# The Rise of Intangible Capital and the Macroeconomic Implications*

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We document a technological change in production technology biased towards intangible capital, such as computerized information and software, over other inputs in the last three decades. This has led to higher investment adjustment costs for firms. A general equilibrium firm dynamics model suggests that this can result in (i) increased firm size and concentration, (ii) changes in aggregate factor shares, and (iii) rise in dispersion of total factor productivity revenue coupled with declining aggregate productivity. This paper provides an alternative mechanism behind these macroeconomic changes in the US economy, emphasizing the efficient response of firms to changes in production technology.

**Keywords:** Intangible Capital, Adjustment Costs, Production Function, Misallocation, Concentration, Labor Share.

**JEL Codes:** D24, D25, E22, O34.

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# 1 Introduction

In the last four decades, expenditures shares of standard factors of production such as tangible capital (Gutiérrez and Philippon, 2017; Alexander and Eberly, 2018) and labor (Elsby, Hobijn and Şahin, 2013) have declined in the US economy. These facts have challenged long-lasting regularities in macroeconomics and spurred a substantial amount of research trying to isolate the causes and consequences of these transformations. Existing explanations attribute these trends to factors like heightened market power, tax changes, demographics, and offshoring.[1]

However, it is now understood that a large part of the aggregate decline in both shares is due to the capitalization of rising intangible capital investment, which increases GDP faster than expenditures on other inputs (Koh, Santaeulàlia-Llopis and Zheng, 2020). These investments have been recognized as part of GDP by the Bureau of Economic Analysis (BEA) in its 1999 and 2013 revisions of accounting standards. Absent these changes, Koh, Santaeulàlia-Llopis and Zheng (2020) show that the observed decline in the labor share would have been substantially smaller, posing a challenge to explanations that either abstract from intangible capital or treat it solely as an intermediate input. This paper offers a complementary explanation to existing theories by linking these trends to changes in firms' cost structures, triggered by an efficient response to shifts in production technology that favor intangible capital.

We proceed in two steps. First, we present three novel facts using firm-level data: (i) the share of intangible inputs in production has risen at the expense of labor; (ii) the investment process in intangible capital is highly frictional; and (iii) the marginal product of intangible capital exhibits greater volatility to shocks and greater dispersion across firms than that of other inputs. Second, a firm dynamics model attributes these characteristics to high fixed and convex adjustment costs for intangible capital. A rise in intangible capital favors larger firms in the selection process, contributing substantially to US secular trends. Additionally, our model indicates that if intangible capital were expensed rather than capitalized, the decline in the labor share would be less severe, in line with the previous literature.

To construct a firm-level measure of intangible capital for 1980-2015, we draw on the corporate finance literature using Compustat.[2] Our measure includes capitalized R&D expen-

[1] See Hopenhayn, Neira and Singhania (2022); Karahan, Pugsley and Şahin (2024) for an explanation emphasizing demographic factors; De Ridder (2024) and De Loecker, Eeckhout and Mongey (2021) for analyses highlighting the role of market power; Kaymak and Schott (2023) for insights on the role of taxation; and Elsby, Hobijn and Şahin (2013) for a discussion of the role of offshoring.

[2] E.g., Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017), and Ewens, Peters and Wang (2025).

ditures and balance sheets identifiable intangible assets. At the aggregate level our measure aligns well compared to Koh, Santaeulàlia-Llopis and Zheng (2020). Like them, we find that investment is mostly driven by non-R&D expenditures, i.e., balance sheet identifiable intangible assets. Thus, while our firm-level measure compares well with established measures, we acknowledge the limitations in accounting standards and systematically account for potential measurement errors in all our computations.[3]

Using this measure, we highlight three stylized facts. First, the input share of intangible capital in production has tripled over the last three decades. Our firm-level production function estimation, encompassing tangible capital, intangible capital, and labor, demonstrates a substantial increase in the input share of intangible capital, rising from 0.03 in 1980 to 0.10 in 2015. Robustness tests, accounting for measurement error and potential overlap between intangible capital input and labor, support this outcome. We call this technological change in the production processes of US firms *intangible capital biased technological change* (IBTC).

IBTC is broadly consistent with the rise in investment in Intellectual property products (IPP) in the national accounting. For instance, ICT investments are one of the fastest growing components of IPP investments as measured by software. They have become dominant input in production as documented by the recent paper by Acemoglu, Anderson, Beede, Buffington, Childress, Dinlersoz, Foster, Goldschlag, Haltiwanger, Kroff et al. (2022). Additionally, this trend aligns with broader international patterns, as studies document similar increases in ICT investment among French firms Lashkari, Bauer and Boussard (2024a) and Korean firms Aum and Shin (2024).

Second, we find that the investment process in intangible capital is impacted by significant frictions. Comparative analysis of firm-level investment processes reveals marked distinctions between intangible and tangible capital. Specifically, intangible capital displays a spike rate (investment rates exceeding 20%) and serial correlation three times larger than tangible capital.[4] These distinctions persist across various factors like industries, periods, firm characteristics, degree of financial frictions, and types of intangible capital, remaining unaffected by measurement errors. These empirical moments have been interpreted by the literature (Cooper and Haltiwanger, 2006) as evidence for both fixed and convex adjustment costs. To

[3]The failure of US Generally Accepted Accounting Principles (US GAAP) to fully account for intangible capital on firms' balance sheets is discussed by Corrado, Hulten and Sichel (2009), Lev and Gu (2016), Ewens, Peters and Wang (2025)

[4]We use a 20% threshold for the spike rate, following the literature, but our results are robust to higher thresholds.

our knowledge, this paper is the first to provide moments of the investment rate distribution for intangible capital, thereby shedding light on the identification of a rich structure of adjustment costs.[5]

Third, we find that the elasticity of the marginal revenue product of intangible capital ($MRPK_I$) to productivity shocks is higher compared to tangible capital ($MRPK_T$), and the within-sector dispersion in $MRPK_I$ exceeds that of $MRPK_T$. These results align with the presence of high investment adjustment costs for intangible capital, impairing the ability of firms to adjust inputs to the desired levels. Thus, preventing the equalization of marginal product to marginal cost, and establishing a correlation with productivity shocks. Importantly, we demonstrate that the excess volatility of $MRPK_I$ is not due to heightened financial frictions, markups, or measurement errors.

Next, we propose a general equilibrium model, extending Hopenhayn (1992) and Clementi and Palazzo (2016a). This model incorporates firms that operate competitively, producing a unique good via a Cobb-Douglas production function utilizing tangible capital, intangible capital, and labor. It incorporates firm entry and exit dynamics, along with flexible investment adjustment costs for both capital types. These costs consist of a convex component influencing intensive margin of investment and a fixed component influencing extensive margin of investment. The model's equilibrium outcomes are constrained efficient, with investment adjustment costs as the sole friction.

The model's predictions on investment dynamics for both capitals depend on specifying parameters for convex and fixed costs. Following Cooper and Haltiwanger (2006) and Asker, Collard-Wexler and De Loecker (2014), we identify fixed costs, which prevent small investments, using spike rates. Convex costs, inducing serial correlation, are pinned down by the autocorrelation in the investment rate process. The calibrated model reveals significant differences in the investment processes, with intangible capital incurring higher fixed and convex adjustment costs than tangible capital.[6] Validations of the model reveal a satisfactory performance on many non-targeted dimensions.

[5]These findings complement Peters and Taylor (2017), Belo, Gala, Salomao and Vitorino (2022), and Cloyne, Martinez, Mumtaz and Surico (2022), who focus only on convex adjustment costs, and those in Akcigit, Celik and Greenwood (2016) and David (2021) focusing on patent transfers and acquisitions respectively.

[6]These results align with case studies on enterprise resource planning (ERP) systems, highlighting substantial implementation costs and extended setup times (Umble, Haft and Umble, 2003; Nicolaou, 2004; Galy and Sauceda, 2014), as well as empirical research showing adjustment costs like behavior of intangible capital (Santoleri, Mina, Di Minin and Martelli, 2024; Bloesch and Weber, 2022).

Quantitatively, IBTC induces a shift in firms' selection, favoring larger firms that are capable of handling the costly investment needs of this new capital. This heightened selection toward larger firms constitutes a substantial driver behind many secular trends in the US economy. Given the model's constrained efficiency, these outcomes represent firms' efficient response to shifts in production technology. Cross-sectoral analysis validates the correlation between intangible capital usage and observed secular trends.

Specifically, IBTC substantially contributes to the rise in average firm size and industry concentration. Its impact steers firms toward relying more on an input with higher adjustment costs, creating barriers to entry and raising the productivity threshold for newcomers. This results in a smaller but more productive pool of firms, rising the average incumbent size. Additionally, high adjustment costs impose growth hurdles for small firms, while higher depreciation rates of intangible capital facilitate easier contraction for larger firms, fostering a shift in sales shares toward the larger firms, thus driving the observed trend in concentration.

Further, IBTC substantially shapes the shifts in aggregate factor shares identified in the literature, producing a rise in the intangible capital share and a decline in both tangible capital and labor shares. Notably, the model explains between 50-75% of the rise in the aggregate intangible capital share and highlights a divergence between micro and macro intangible capital shares. At the micro-level, there's a 7 percentage point (p.p.) increase, from 3% to 10%, while at the macro-level, there's a 2-3 p.p. rise. This divergence is due to adjustment costs acting as a constraint, limiting investments in intangible capital by firms despite large changes in production technology.

Moreover, IBTC leads to a similar decline as in the data of the tangible capital investment rate. This happen because, while the firm-level tangible capital share stays constant, IBTC intensifies the selection process towards older, larger firms with lower investment rates. Additionally, IBTC leads to a 5-7 percentage point decline in the aggregate labor share, accounting for 62-87% of its delcine. In line with Koh, Santaeulàlia-Llopis and Zheng (2020), we demonstrate that treating intangible capital investment as an expense—rather than capitalizing it—would significantly reduce the observed decline in the labor share. This underscores the importance of treating intangible capital as a dynamic input whose investment behavior is central for the evolution of GDP. Without this treatment, the model would fail to explain why the BEA's revision of accounting standards resulted in such a substantial revision of the measured labor share. Further, as the selection process heightens, allowing only more productive firms to operate, there's an increase in the firm-level profit rate, consistent with De Loecker, Eeckhout and Unger (2020) and Barkai (2020).

Finally, the quantitative model shows that IBTC can explain between 20-40% of the overall rise in the dispersion in $TFPR$, as documented by Bils, Klenow and Ruane (2021). This is driven by the fact that $TFPR$ in our framework is a weighted geometric mean of the marginal revenue product of inputs, where the weights are proportional to their output elasticities. The presence of adjustment costs means that dispersion in $TFPR$ is driven by dispersion in the marginal revenue products of both types of capital. When the output elasticity of intangible capital increases, the dispersion in $MRPK_I$ becomes the primary driver of the dispersion in $TFPR$. We show that, in the model, this effect also translates into a decline in aggregate productivity. Although selection forces tend to increase aggregate productivity, this effect is quantitatively dominated by a weakening correlation between firm size and productivity due to rising adjustment costs.

We conclude by emphasizing two points. First, our model does not interpret any of the aforementioned trends as signals of inefficiency, since the allocation remains consistent with the planner's optimal allocation. This suggests a more benign interpretation of these phenomena and indicates that efficient explanations can potentially account for a substantial portion of the observed secular trends. Second, despite its success in matching many aggregate secular trends in the US—both qualitatively and quantitatively, the model falls short in explaining the decline in business dynamism. This implies that forces beyond rising intangible capital investment may have been at play during the period of interest, potentially playing a significant role in the decline in business dynamism, such as the rise in market power in De Loecker, Eeckhout and Unger (2020), the demographic changes as in Karahan, Pugsley and Şahin (2024), or the rise in offshoring discussed in Elsby, Hobijn and Şahin (2013).

*Related Literature.* This paper builds on the literature that measures intangible capital at the firm level, as in Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017), Eisfeldt, Falato and Xiaolan (2023), and Ewens, Peters and Wang (2025).[7] Building on these measures, we estimate the firm-level production function documenting the increase in the share of this

[7] The paper relates to the literature measuring intangible capital at the aggregate level, as in Corrado, Hulten and Sichel (2009), Koh, Santaeulàlia-Llopis and Zheng (2020), Atkeson and Kehoe (2005), Corrado and Hulten (2010), McGrattan and Prescott (2010a), McGrattan and Prescott (2010b), McGrattan and Prescott (2014), and Atkeson (2020).

input over time and emphasize the significance of both fixed and convex adjustment costs for its investment process and marginal product.

Furthermore, our paper is related to the extensive literature that examines quantitatively frictional investment dynamics, as in Cooper and Haltiwanger (2006) and Asker, Collard-Wexler and De Loecker (2014), highlighting the role of fixed adjustment costs.[8] Peters and Taylor (2017), Belo, Gala, Salomao and Vitorino (2022) and Cloyne, Martinez, Mumtaz and Surico (2022) structurally estimate convex adjustment costs finding them to be large for intangible relative to tangible capital.[9] We provide firm-level empirical evidence for the presence of such frictions, showing that also fixed adjustment costs are necessary to rationalize the firm-level distribution of intangible capital investment.

This paper is particularly close to Aghion, Bergeaud, Boppart, Klenow and Li (2023), Autor, Dorn, Katz, Patterson and Van Reenen (2020), Chiavari (2021), Hsieh and Rossi-Hansberg (2023), and Lashkari, Bauer and Boussard (2024b), who focus on technological features—unrelated to intangible capital—behind similar phenomena and present a more benign view of the recent trend in concentration. It also complements studies such as Akcigit and Ates (2021, 2023), Castro-Vincenzi and Kleinman (2022), Cavenaile, Celik and Tian (2019), Covarrubias, Gutiérrez and Philippon (2020), De Loecker, Eeckhout and Mongey (2021), Elsby, Hobijn and Şahin (2013) Hopenhayn, Neira and Singhania (2022); Karahan, Pugsley and Şahin (2024), Hubmer (2023), Kaymak and Schott (2023), and Olmstead-Rumsey (2019), which explore mechanisms unrelated to changes in firm-level production processes contributing to some of the secular trends in aggregate factor shares we study. Since none of the aforementioned papers focuses on intangible capital as a dynamic input, they cannot directly address the finding in Koh, Santaeulàlia-Llopis and Zheng (2020) that much of the decline in the labor and tangible investment shares is attributable to rising intangible capital investment.

In relation to the literature on intangible capital, our paper differs in its focus as its main mechanism does not rely on intangibles driving market power as in De Ridder (2024) and Weiss (2019) or financial frictions as in Falato, Kadyrzhanova, Sim and Steri (2022) and Zhang (2019).[10] Our study contributes by using micro-level data to reveal novel properties of intan-

[8]Other papers in this literature are Abel and Eberly (1994), Abel and Eberly (1996), Doms and Dunne (1998), Khan and Thomas (2008) Asker, Collard-Wexler and De Loecker (2014), Clementi and Palazzo (2016a), and Winberry (2021).

[9]Akcigit, Celik and Greenwood (2016) and David (2021) focusing on patent transfers and acquisitions respectively suggest the presence of irreversibility and trading frictions.

[10]Other studies explore various aspects of intangible capital. Caggese and Pérez-Orive (2022) and Döttling and

gible capital and showing that a substantial portion of these trends arises from the economy's *efficient* response to shifts in firm-level production technology—rather than the rise of inefficiencies related to market power and financial frictions.

*Outline.* Section 2 discusses the data and the variables' construction. Section 3 documents the stylized facts. Section 4 presents the model. Section 5 contains the calibration and its external validation, and Section 6 discusses the mechanisms. Section 7 presents the implications of IBTC, and Section 8 concludes.

# 2 Data and Intangible Capital Measurement

## 2.1 Main Measures

The main data source is Compustat, a firm-level database with all the US publicly traded firms between 1980 and 2015. This section discusses this dataset, while Online Appendix I.I provides more details on the data cleaning process. The choice of the data is driven by its ability to cover the period of interest and the largest number of sectors. These characteristics make these data a good source to study technological changes in production undertaken by US firms.

Although publicly traded firms are few relative to the total number of firms, they are the largest firms in the economy, accounting for roughly 30% of US employment (Davis, Haltiwanger, Jarmin, Miranda, Foote and Nagypal, 2006). The Compustat data contain information on firm-level financial statements including sales, input expenditures, and capital stock information, as well as a detailed industry activity classification.

As a measure of firm-level production, we use sales (SALE); as a measure of variable inputs used in production, we use cost of goods sold (COGS); as a measure of firm-level employees, we use (EMP); as a measure of tangible capital, we use gross capital (PPEGT); and as a measure of overhead costs, we use selling, general, and administrative expenses XSGA. Summary statistics related to these variables are reported in Online Appendix I.I.

Consistently with the accounting standards and with the model presented in Section 4,

Ratnovski (2023) find slow responsiveness to monetary policy. Bates, Kahle and Stulz (2009), Brown, Fazzari and Petersen (2009), and Altomonte, Favoino, Morlacco and Sonno (2021) note its low collateral value. Griliches (1995) and Doraszelski and Jaumandreu (2013) investigate intangible capital's contribution to productivity.

these variables can be mapped into the following cost structure:

$$W\ell + x_T + x_I + \mathcal{C}(x_T, x_I) + c_f, \tag{1}$$

where, $W\ell$ is the wage bill or the variable input expenditure, $x_T$ is investments in tangible capital, $x_I$ is investments in intangible capital (described below), $\mathcal{C}(\cdot)$ are the adjustment costs, and $c_f$ is the overhead cost. Adjustment costs, with overhead costs, are considered residual expenditures accounted in the data in XSGA. This choice is consistent with the assumptions used to construct intangible capital and with the US accounting standards practice.[11]

## 2.2 Intangible Capital Measurement

The measurement of intangible capital is challenging because, under US GAAP, a substantial portion of internally generated intangible capital is expensed (Lev and Gu, 2016; Ewens, Peters and Wang, 2025). Only a few exceptions—often related to software—are permitted to be capitalized on the balance sheet, in addition to externally acquired intangible capital. Online Appendix I.I.III discusses existing accounting standards, the treatment of software, and the associated challenges in measuring firm-level intangible capital.

In line with these considerations, and following the approach of Peters and Taylor (2017) and Ewens, Peters and Wang (2025), our primary measure comprises internally generated intangible capital that is expensed, as well as balance sheet intangible capital.[12] Internally generated intangible capital that is expensed is obtained through the capitalization of R&D expenditure (XRD) via perpetual inventory method, as in national accounting practice (Corrado, Haskel, Jona-Lasinio and Iommi, 2022):

$$k_{R\&D,ft} = (1 - \delta_s)k_{R\&D,ft-1} + \text{XRD}_{ft}, \tag{2}$$

where XRD is the gross investment in knowledge capital deflated by the IPP price deflator, the

[11] In Compustat data, it is often assumed that the capital adjustment costs are expensed in XSGA, because accounting standards treat them as a residual expenditure item, where all non-production expenditures are accounted for.

[12] We exclude organizational capital measured through XSGA capitalization. XSGA includes various expenditures unrelated to intangible capital, like CEO wage, building rents, and tangible and intangible capital adjustment costs. Capitalizing it might bias the intangible capital investment rate, as XSGA is never zero. Including organizational capital would also inflate our intangible capital measure, capitalizing adjustment costs and raising conceptual issues in estimating the production function.

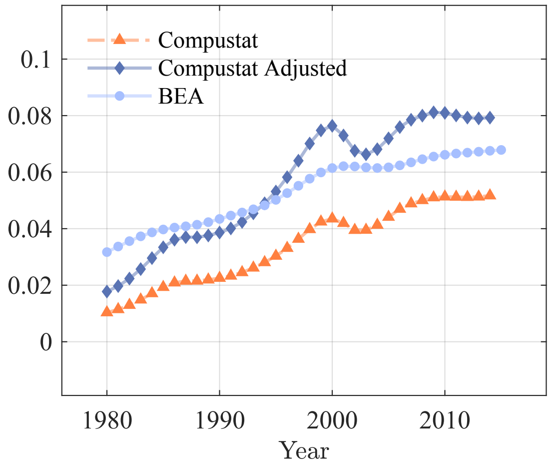
sector-level depreciation rate $\delta_s$ is taken from Ewens, Peters and Wang (2025), and the initial stock is assumed to be zero.[13]

The second component of intangible capital is the balance sheet intangible capital, given by

$$k_{BS,ft} = \text{INTAN}_{ft} + \text{AM}_{ft} - \text{GDWL}_{ft}, \tag{3}$$

where INTAN is *net* intangible capital, AM is its amortization, and GDWL represents goodwill. We sum net balance sheet intangible capital with its amortization to get a gross measure comparable to PPEGT. We drop goodwill because of measurement issues extensively explained in Online Appendix I.I.III. However, our empirical analysis demonstrates that the results remain robust even when a fraction of goodwill is included. Adding this measure is important because, in addition to capturing most externally acquired intangible capital, it includes capitalized software developed in-house, which is one of the most significant intangible capital investments in the national accounts (see Online Appendix I.I.III for further details).

**Figure 1: Aggregate Intangible Investment Share: Compustat vs BEA**




The figure reports the evolution of the intangible investment share. The dashed orange line with triangles shows the intangible investment share in Compustat, calculated as total investment in intangible capital divided by total sales. The dark blue line with diamonds displays the adjusted intangible investment share in Compustat, computed as intangible capital investment divided by total sales net of the material bill (gross value added). The solid light blue line with circles represents the intangible investment share from the BEA corporate non-financial sector, calculated as intangible capital investment to GDP net of proprietary income, taxes, and subsidies following Koh, Santaeulàlia-Llopis and Zheng (2020). Material bill in Compustat is COGS $-$ XLR (with XLR replaced by its sectoral mean if missing), i.e., total variable costs net of labor cost. The data are detrended using an HP filter with $\lambda = 6.25$.

[13]For our analysis we exclude all observations in the first five years to avoid a strong dependence of our results on the initial condition for knowledge capital. Although results are not sensitive to this exclusion.

Thus, our final measure of firm-level intangible capital is given by

$$k_{I,ft} = k_{R\&D,ft} + k_{BS,ft}. \tag{4}$$

Figure 1 compares our intangible capital investment share with BEA's from Koh, Santaeulàlia-Llopis and Zheng (2020). Both show a similar increase over time. In the Online Appendix I.I.IV, we provide additional comparisons between our firm-level measure and national accounting measures and highlight that both at the firm and aggregate levels, the primary driver of intangible capital rise is the externally acquired component.[14] Despite these successes, we acknowledge the possibility of measurement error, addressing it in our empirical analysis to minimize bias in our findings.

# 3 Empirical Analysis

This section presents the three main empirical results of the paper.

## 3.1 Fact 1: Intangible Capital Share Has Tripled since 1980

### 3.1.1 Production Function Estimation

We estimate the log Cobb-Douglas firm-level production function, given by

$$q_{ft} = \alpha k_{T,ft} + \nu k_{I,ft} + (1 - \alpha - \nu)\ell_{ft} + \omega_{ft} + \varepsilon_{ft}, \tag{5}$$

where $q_{ft}$ is the log of output, $k_{T,ft}$ is the log of tangible capital, $k_{I,ft}$ is the log of intangible capital, $\ell_{ft}$ is the log of labor, $\omega_{ft}$ is the log of productivity, and $\varepsilon_{ft}$ is the error term.[15] The introduction of intangible capital as an input in production is motivated by the growing evidence that software, and intangible capital more generally, are extensively used in production (Bhandari and McGrattan, 2021; Acemoglu, Anderson, Beede, Buffington, Childress,

[14] While we follow the corporate finance literature mirroring national accounting practice in constructing the stock of intangible capital from costs, a complementary strand of the literature concentrating on growth has focused on measuring the outcomes of the R&D efforts of firms, namely patents. We find that firm-level patents are highly correlated with our intangible capital measure. Results are available upon request.

[15] Practically, as output we use the firm's sales; as tangible capital we use gross property, plant, and equipment; as intangible capital we use the measure constructed in Section 2; and as labor we use the total firm-level number of employees.

Dinlersoz, Foster, Goldschlag, Haltiwanger, Kroff et al., 2022).

To estimate the variation in input shares over time, we assume firm-level returns to scale are 1 and all firms share a common technology (below we show that these assumptions are inconsequential). Estimating firm-level production functions is difficult due to unobservable productivity ($\omega_{ft}$). To address this endogeneity, we use two approaches from the empirical industrial organization literature: the cost shares (CS) approach (Foster, Haltiwanger and Syverson, 2008) and the Ackerberg-Caves-Frazer (ACF) approach (Ackerberg, Caves and Frazer, 2015). Details on both methodologies and associated challenges are in Online Appendix I.II.

We estimate equation (5) with both methodologies over 1980-2015 using 10-year rolling windows.[16] Figure 2 presents the results. Solid orange lines with triangles show ACF estimates, while dashed light blue lines with circles show CS estimates with 99% confidence intervals. Notably, all the action comes from intangible capital and labor, while tangible capital exhibits no clear trend over the period.

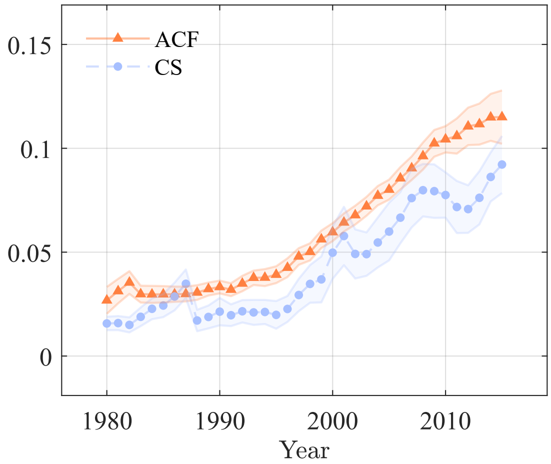
Specifically, the intangible capital share, using the CS approach, increases from 0.02 in 1980 to 0.09 in 2015, while with the ACF approach, it rises from 0.03 to 0.11. The share of labor in production, following the CS approach, declines from 0.759 to 0.639, while with the ACF approach, it drops from 0.686 to 0.521. These results indicate a significant transformation in US firms' production technology—a phenomenon that we call *intangible capital biased technological change* (IBTC).

The labor share trend aligns with findings in the literature, as observed in Elsby, Hobijn and Şahin (2013), Karabarbounis and Neiman (2013), Koh, Santaeulàlia-Llopis and Zheng (2020), among others. Particularly, the decline began in the late 1990s and accelerated after 2005. Differences between micro and aggregate-level measures may stem from investment frictions hindering the transmission of micro to macro changes, as explained later in Section 7.

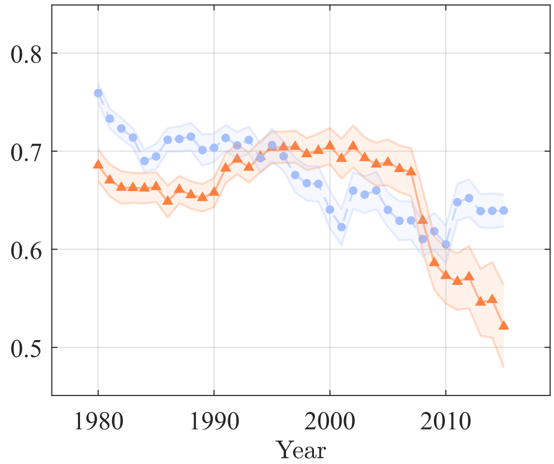
In Online Appendix II.II we show that alternative assumptions about the nature of intangible capital—whether it acts as a productivity shifter or a demand shifter—are isomorphic to the strategy outlined above. Moreover, Online Appendix I.III presents a host of robustness checks, including the following alternative specifications: (i) unconstrained returns to scale; (ii) imposing decreasing returns to scale; (iii) technology at the two-digit sector level (NAICS 2); (iv) a translog production function; (v) using cost of goods sold as a variable input; (vi) ex-

[16] I.e, we keep all the observations in the interval $\left[\max\left(T_{\min}, t-5\right), \min\left(t+5, T_{\max}\right)\right], \forall t \in [T_{\min}, T_{\max}]$.

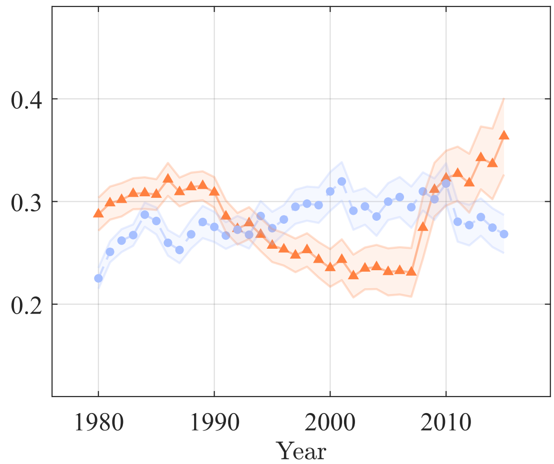
**Figure 2: Trends in Input Shares**




**(a) Intangible Capital Share**




**(b) Labor Share**




**(c) Tangible Capital Share**

Note. The figures present the output elasticities estimated with the cost shares (CS) approach (dashed light blue lines with circles) and with the Ackerberg-Caves-Frazer (ACF) approach (solid orange lines with triangles). The elasticities are estimated using 10-year rolling windows over time. Bands around the point estimates report the 99% confidence intervals.

cluding internally generated intangible capital ($k_{R\&D}$); (vii) including goodwill in the measure of balance sheet intangible capital; (viii) using an alternative deflator for intangible capital; (ix) accounting for output and input price variation in the ACF estimation; and (x) controlling for measurement error in intangible capital. All of these specifications lead to similar quantitative conclusions, confirming that the rise in intangible capital at the expense of labor in production is a robust feature of the data.

### 3.2 Fact 2: Intangible Investment Faces Higher Investment Frictions Relative to Tangible Investment

#### 3.2.1 Investment Rate Distributions

The investment rate of each type of capital is defined as

$$\frac{x_{j,ft}}{\frac{1}{2}(k_{j,ft}+k_{j,ft-1})} \equiv \frac{k_{j,ft}-k_{j,ft-1}}{\frac{1}{2}(k_{j,ft}+k_{j,ft-1})} + \delta_j, \quad j \in \{T, I\}, \tag{6}$$

where $\delta_j$ is the depreciation rate, $x_{j,ft}$ is investment, and $k_{j,ft}$ is capital.[17] Following Cooper and Haltiwanger (2006) and Clementi and Palazzo (2019), we construct a balanced panel of firms from 1980 to 1990 to study the properties of investment rates.[18] Following common practice, we also drop observations where the total value of acquisitions relative to total assets exceeds 5%.[19] Finally, we drop firms that have *never* invested in intangible capital, avoiding the comparison between firms that never invest to the ones that invest in intangible capital.

Figure 3a and 3b depict investment rate distributions for intangible and tangible capital, respectively (Table 1 summarizes key distribution moments). Notably, intangible capital exhibits a higher average investment rate than tangible capital (34% vs. 11%), partially reflecting its elevated depreciation rate. Moreover, the inaction rate, i.e., the fraction of investment below 1% in absolute value, is higher for intangible capital (10% vs. 3%) and also the positive spikes, i.e., periods of investment above 20%, is higher (76% vs.19%).[20] Finally, also the serial correlation of intangible capital is higher (autocorrelation of 0.31 vs. 0.11).

Differences in the investment dynamics between intangible and tangible capital, marked by higher positive spike rates, inaction rates, and serial correlation for intangible capital, are indicative of greater investment frictions. Prior research interprets such patterns as evidence of elevated adjustment costs (Cooper and Haltiwanger, 2006; Asker, Collard-Wexler and De Loecker, 2014; Clementi and Palazzo, 2016a). Focusing on *spike rates* and *serial corre-*

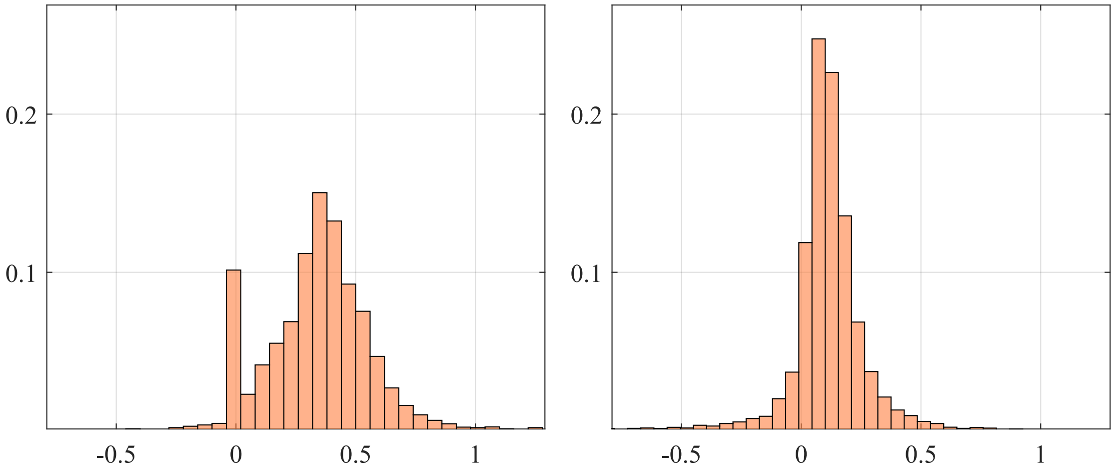
[17] The depreciation rate for tangible capital is 7%, while for intangible capital, it follows the description in Section 2 for its knowledge capital components and is set at 20% for its externally acquired component.

[18] This balanced panel accounts for selection dynamics linked to entry and exit. We concentrate on the 1980-1990 period, aligning with the initial steady-state calibration of our model and the onset of the secular trends under investigation. The empirical distribution, however, remains consistent across different time frames.

[19] This precaution mitigates biases from acquisitions, which leads to a large investment for one firm without an equivalent disinvestment for the other. In our sample, such instances form a small proportion of all entries.

[20] Aligning with the tangible capital literature, we adopt a 20% threshold for the spike rate, ensuring comparability. However, doubling the spike rate threshold to 40% still yields a spike rate of 38%, almost twice as large as for tangible.

**Figure 3: Investment Rate Distributions**




**(a) Intangible Capital** **(b) Tangible Capital**

Note. The figures report the investment rate distributions of intangible and tangible capital for a balanced panel of firms between the years 1980 and 1990. Figure 3a shows the investment rate distribution for intangible capital. Figure 3b shows the investment rate distribution for tangible capital. The histograms are constructed by dropping from the balanced panel all the firms that never invested in intangible capital and all the observations with investment rates above 3 or below -1. Results are robust to other winsorization schemes.

*lation*, as inaction rates are challenging to measure for capital investments (Winberry, 2021), these moments are associated with fixed and convex investment adjustment costs.[21] A high positive spike rate suggests non-convexities due to fixed costs, where firms undertake large projects, while a high serial correlation indicates convex adjustment costs, reflecting firms' efforts to smooth investments over time.

Our findings on intangible capital investment behavior align with recent micro empirical evidence (Santoleri, Mina, Di Minin and Martelli, 2024; Bloesch and Weber, 2022).[22] The former, examining R&D subsidies, indicates heightened responsiveness of intangible capital investment to costs, implying underlying frictions such as adjustment costs. The latter demonstrates that congestion in onboarding new workers contributes to these costs. These findings align with the notion that intangible capital, being firm-specific with an underdeveloped secondary market, faces trade frictions, contributing to high adjustment frictions (Haskel and Westlake, 2018).

In Online Appendix I.IV we demonstrate the robustness of two key features in the invest-

[21] The high rate of inaction in intangible capital seems to be driven by internally generated intangible capital, making it unclear if this is an intrinsic property of intangible capital overall. We thank an anonymous referee for pointing out this feature of the data.

[22] Our findings also support the case studies from the operational research literature documenting how investment in ERP systems entails very high adjustment frictions, such as long setup time and workforce training (Umble, Haft and Umble, 2003; Nicolaou, 2004; Galy and Sauceda, 2014).

**Table 1: Investment Rates Moments**

| Investment rates | Intangible | Tangible |
|---|---|---|
| Average | 0.34 | 0.11 |
| Positive fraction, $i > 1$ | 0.88 | 0.87 |
| Negative fraction, $i < -1$ | 0.02 | 0.10 |
| Inaction rate | 0.10 | 0.03 |
| Spike rate, $\|i\| > 20$ | 0.77 | 0.22 |
| Positive spikes, $i > 20$ | 0.76 | 0.19 |
| Negative spikes, $i < -20$ | 0.01 | 0.03 |
| Standard deviation | 0.26 | 0.17 |
| Serial correlation, Corr$(i_t, i_{t-1})$ | 0.31 | 0.09 |

Note. This table shows the moments of the investment rate distribution of intangible and tangible capital. The statistics are computed for a balanced panel of firms between 1980 and 1990.

ment rate distribution of intangible capital: higher positive spike rates and serial correlation compared to tangible capital. These characteristics appear intrinsic to intangible capital investment and do *not* seem to depend on the (i) industry; (ii) period; (iii) firm characteristics (age, size) and degree of financial frictions (leverage, liquidity); (iv) types of intangible capital; (v) specifications for calculating investment rates; (vi) the presence of measurement error; (vii) the addition of Goodwill to the measure of intangible capital; and (viii) the use of alternative deflators .[23] In the quantitative section, we leverage these two moments to identify underlying investment frictions associated with intangible capital investment.

## 3.3 Fact 3: Intangible Capital Has Higher Dispersion and Responsiveness of Marginal Revenue Product Relative to Tangible Capital

### 3.3.1 Responsiveness of $MRPK_I$ and $MRPK_T$

Evaluating the marginal revenue product of capital responsiveness to productivity shocks, we follow Asker, Collard-Wexler and De Loecker (2014). Without investment frictions, the marginal revenue product of capital remains unchanged in response to productivity shocks, equating to the user cost of capital. Conversely, with investment frictions, such as adjust-

[23] Stock patent changes exhibit similar patterns to those highlighted in this section. Results are available upon request.

ment costs, the marginal revenue product of capital responds to productivity shocks without equating the user cost of capital, as investment is constrained. Thus, if intangible capital faces greater frictions than tangible capital, we expect a stronger correlation between the marginal revenue product of intangible capital and productivity shocks.

To test the prediction, we compute the log of the marginal revenue product in line with production technology (5) as

$$\log MRPK_{j,ft} \propto \log y_{ft} - \log k_{j,ft}, \quad j \in \{T, I\}, \tag{7}$$

where $y_{ft}$ is firm-level output and $k_{j,ft}$ is firm-level capital. Equation (5) holds in the presence of a Cobb-Douglas production function.[24] Our regression framework is given by

$$\log MRPK_{j,ft} = \gamma_1 \varepsilon_{ft} + \mathbf{\Gamma X_{ft-1}} + \gamma_f + \gamma_t + \nu_{ft}, \quad j \in \{T, I\}, \tag{8}$$

where $\varepsilon$ is the innovation to log $TFPR$, i.e., total factor productivity revenue.[25] $\mathbf{X}$ is a vector of controls (capital $j$, $TFPR$, age, size, leverage and liquidity), $\gamma_f$ is a firm fixed effect, and $\gamma_t$ is a time fixed effect.[26] The coefficient of interest is $\gamma_1$. Without frictions, the marginal revenue product of capital is constant, i.e., $\gamma_1 = 0$. Higher distortion leads to a greater response to productivity shocks, i.e., $\gamma_1 > 0$.

Moreover, considering recent work on potential measurement errors in marginal revenue products (Gollin and Udry, 2021; Bils, Klenow and Ruane, 2021), we highlight that our regression accommodates both iid and fixed measurement errors in firm-level marginal revenue products. Additionally, to address autocorrelated measurement errors in both capital's marginal revenue, we assume observed $MRPK_{ft} = e^{\omega_{ft}} MRPK^*_{ft}$, with serially correlated $\omega$, given by

$$\omega_{ft} = \rho \omega_{ft-1} + \eta_{ft}, \tag{9}$$

where $\eta$ is the iid shocks. Substituting (9) in (8) and $\rho$-differentiating it we obtain the following

[24] In our regression framework with firm- and time-fixed effects, our results are valid for more general production functions with elasticities varying at the firm level and over time.

[25] To calculate $\varepsilon_{ft}$, we regress $\log TFPR_{ft}$ on itself lagged ($\rho_p$), firm fixed effects, and time fixed effects. The innovation to revenue productivity at the firm level is then computed as $\varepsilon_{ft} = \log TFPR_{ft} - \widehat{\rho}_p \cdot \log TFPR_{ft}$.

[26] Controls enable the comparison of firms with similar characteristics and degrees of financial frictions, as captured by leverage and liquidity. Individual-fixed effects absorb any permanent heterogeneity, while time-fixed effects absorb aggregate variation.

alternative specification:

$$\log MRPK_{j,ft} = \rho \log MRPK_{j,ft-1} + \gamma_1(\varepsilon_{ft} - \rho\varepsilon_{ft-1}) \\ + \mathbf{\Gamma X_{ft-1}} - \rho\mathbf{\Gamma X_{ft-2}} + \gamma_f + \gamma_t + \eta_{ft} + \nu_{ft}, \quad j \in \{T, I\}. \tag{10}$$

**Table 2: Heterogeneous Response of $MRPK_T$ and $MRPK_I$ to $TFPR$ Shocks**

| | Baseline | | Measurement Error Adjusted | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable | $MRPK_{T,ft}$ | $MRPK_{I,ft}$ | $MRPK_{T,ft}$ | $MRPK_{I,ft}$ |
| $\varepsilon_{ft}$ | 1.01*** | 1.27*** | 0.96*** | 1.28*** |
| | (0.00) | (0.01) | (0.00) | (0.01) |
| Time dummies | ✓ | ✓ | ✓ | ✓ |
| Firm dummies | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Observations | 88,964 | 88,964 | 80,485 | 80,485 |

Notes. We report the coefficients from the regressions of marginal revenue product of tangible capital, $MRPK_{T,ft}$, and marginal revenue product of intangible capital, $MRPK_{I,ft}$, on revenue productivity shocks, $\varepsilon_{ft}$. The controls include capital, revenue productivity, sales, leverage, and liquidity. The baseline specification, which controls for classical (fixed and iid) measurement error, is shown in equation (8). The alternative specification, which controls for serially correlated measurement error, is presented in equation (10). Standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

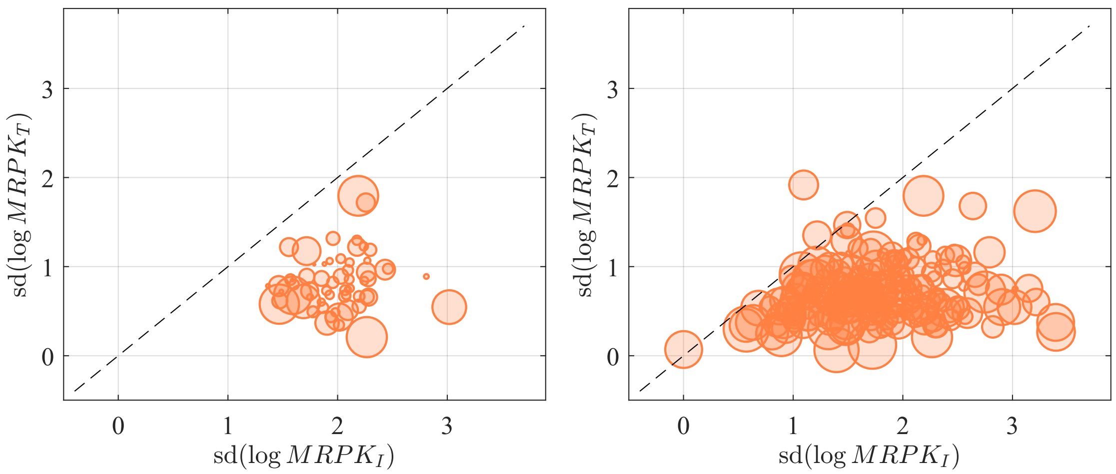
Table 2, columns 1-2 depict regression coefficients from the baseline specification (8), while columns 3-4 display coefficients from the alternative specification (10). Notably, both tangible and intangible capital's marginal revenue product responds positively to revenue productivity shocks ($\gamma_1$ significantly greater than 0 in all specifications). Importantly, intangible capital exhibits a stronger reaction, reinforcing our prior findings of higher investment frictions, like adjustment costs, compared to tangible capital. This outcome holds even when considering firm fixed effects and variations in capital, revenue, productivity, age, size, leverage, and liquidity. It suggests that intangible capital's higher frictions are inherent, not solely driven by financial constraints or different firm compositions.

Online Appendix I.V demonstrates that adjusting our measure of marginal revenue products for markups—thereby ruling out the possibility that the shock response we observe is driven by them—does not alter our conclusions. This confirms the robustness of the finding that the marginal revenue product of intangible capital is significantly more responsive to productivity shocks.

### 3.3.2 Relative Dispersion of $MRPK_I$ and $MRPK_T$

We explore the connection between investment frictions and relative cross-sectional dispersion in the $MRPK_I$ and $MRPK_T$. In the presence of frictions like adjustment costs, the marginal revenue product deviates from the user cost, creating variation across firms. These differences are due to the frictional capital adjustment after a productivity shock. Intangible capital, subject to higher frictions than tangible capital, is expected to exhibit more dispersed marginal revenue products.

**Figure 4: Sector-Level Dispersion in $MRPK_I$ and $MRPK_T$**




**(a) SIC2 Level** **(b) SIC3 Level**

Note. The figures show the standard deviation of $MRPK_I$ ($x$-axis) and the standard deviation of $MRPK_T$ ($y$-axis). Standard deviations are calculated within sectors and averaged across the years. Marginal revenue products are constructed as described in the text. The dashed black line shows the 45-degree line. Figure 4a is constructed calculating standard deviations at the SIC2 level; each circle represents a SIC2 sector, where the size of the circle is proportional to its size (sale weighted) in Compustat. Figure 4b is constructed calculating standard deviations at the SIC3 level; each circle represents a SIC3 sector, where the size of the circle is proportional to its size (sale weighted) in Compustat.

Figure 4 shows the scatter plot of sector-level standard deviations of $MRPK_I$ against $MRPK_T$ calculated at SIC2 and SIC3 levels. Intangible capital consistently displays higher dispersion than tangible capital in the majority of sectors.[27] This finding supports the presence of higher investment friction like adjustment costs associated with intangible capital

[27] Since measurement error in marginal products is mostly over time (Bils, Klenow and Ruane, 2021), taking time averages mitigates concerns about results being solely driven by measurement error.

investment compared to tangible capital investment.

Online Appendix I.V shows that even adjusting for variation in markups across firms, intangible capital consistently exhibits greater marginal product dispersion than tangible capital across sectors.

# 4 Theoretical Framework

This section presents and discusses the model.

## 4.1 Model

*Environment.* Time is discrete and indexed by $t = 1, 2, \ldots$. At the time $t$, a positive mass of price-taking firms produce a homogeneous good utilizing the production function $y = e^z \left(k_T^\alpha k_I^\nu \ell^{(1-\alpha-\nu)}\right)^\omega$, with $\alpha, \omega, \nu$ in $(0, 1)$, where $k_T$ denotes tangible capital, $k_I$ is intangible capital, $\ell$ is labor, and $z$ is idiosyncratic random productivity. Idiosyncratic productivity $z$ is driven by the stochastic process

$$z' = \rho_z z + \sigma_z \varepsilon',$$

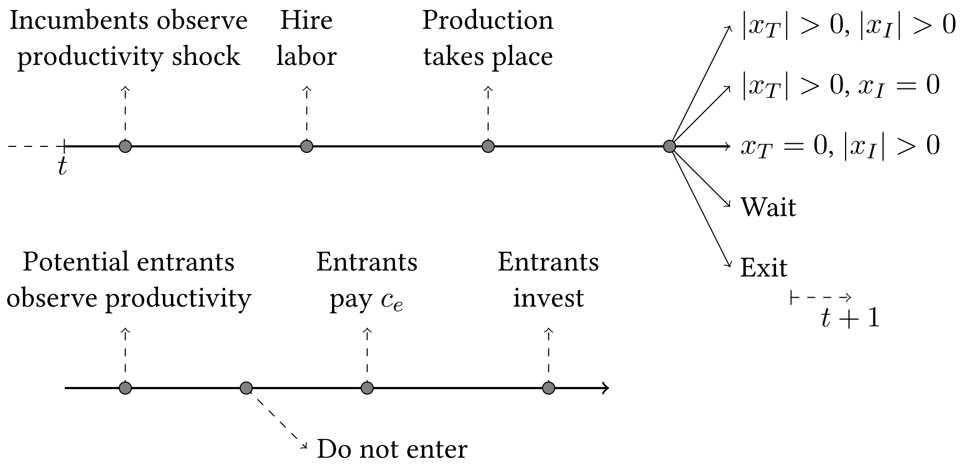
where $\varepsilon \sim \mathcal{N}(0, 1)$. The conditional distribution of $z$ is denoted by $\Gamma(z'|z)$.

Firms discount future profits using the time-invariant discount factor $\frac{1}{R}$, $R > 1$. Tangible capital depreciates at a rate $\delta_T \in (0, 1)$, whereas intangible capital depreciates at a rate $\delta_I \in (0, 1)$. Adjusting the tangible capital stock by $x_T$ and the intangible capital stock by $x_I$ bears the cost

$$\mathcal{C}(x_T, x_I; k_T, k_I) = \frac{\gamma_T}{2}\left(\frac{x_T}{k_T}\right)^2 k_T + \frac{\gamma_I}{2}\left(\frac{x_I}{k_I}\right)^2 k_I + \mathbf{1}\{x_T \neq 0\} f_T k_T + \mathbf{1}\{x_I \neq 0\} f_I k_I,$$

where $\gamma_T, \gamma_I, f_T, f_I \in \mathbf{R}^+$. We allow for two different kinds of adjustment costs: convex and fixed. Non-convex costs capture increasing returns to new capital installation, the need for plant restructuring, and worker retraining. While not admitting irreversibility, our formulation of nonconvex costs can capture a form of partial irreversibility, as disinvestment bears an output cost. Convex costs take into account expenses for overtime, inventory, and machine setup. Additionally, we assume these costs are proportional to the capital stock, addressing size effects. Finally, adjustment costs are paid in terms of final output.

**Figure 5: Timing in the Model**




We assume that the demand for a firm's output and the supply of both types of capital are infinitely elastic, and we normalize their prices to 1 (Khan and Thomas, 2008; Clementi and Palazzo, 2016a). Each period, operating firms incur a fixed cost $c_f > 0$. Firms that quit production cannot reenter the market at a later stage and recoup the un-depreciated part of their capital stocks, net of the adjustment cost.

There is a constant exogenous mass $m > 0$ of prospective entrants, each of which receives an initial productivity $s$, with $s \sim \Lambda(s)$, a Pareto distribution with scale parameter $\eta$. Conditional on entry, the distribution of the idiosyncratic shock in the first period of operation is $\Gamma(z'|s)$, strictly increasing in $s$. Effective entrants must pay an entry cost $c_e \geq 0$. The supply of labor is given by $L(W) = W^{\psi}$, where $\psi > 0$ and $W \in \mathbf{R}^{+}$ is the real wage.[28]

Finally, in each period, the stationary distribution of operating firms over the three dimensions of heterogeneity is denoted by $\Omega(z, k_T, k_I; W)$. The timing of the model is presented in Figure 5.

*Incumbents problem.* Given idiosyncratic productivity $z$, tangible capital $k_T$, and intangible capital $k_I$, the profits of an incumbent are

$$\pi(z, k_T, k_I; W) = \max_{\ell}\ e^{z}\left(k_T^{\alpha} k_I^{\nu} \ell^{(1-\alpha-\nu)}\right)^{\omega} - W\ell. \tag{11}$$

Upon exit, a firm obtains the un-depreciated portion of its tangible capital $k_T$ and intangible

[28]We are assuming that the representative household's utility, following Clementi and Palazzo (2016a) and Carvalho and Grassi (2019), is given by $u(C, L) = C - \frac{L^{1+1/\psi}}{1+1/\psi}$.

capital $k_I$, net of the adjustment costs:

$$\mathcal{V}_x(k_T, k_I) = (1-\delta_T)k_T + (1-\delta_I)k_I - \mathcal{C}(-(1-\delta_T)k_T, -(1-\delta_I)k_I; k_T, k_I).$$

Then, the start-of-period value of an incumbent firm is dictated by the function $\mathcal{V}(z, k_T, k_I; W)$, which solves the following functional equation:

$$\begin{aligned}\mathcal{V}(z, k_T, k_I; W) = \pi(z, k_T, k_I; W) + \max\{&\mathcal{V}_x(k_T, k_I), \tilde{\mathcal{V}}_1(z, k_T, k_I; W) - c_f, \\ &\tilde{\mathcal{V}}_2(z, k_T, k_I; W) - c_f, \tilde{\mathcal{V}}_3(z, k_T, k_I; W) - c_f, \tilde{\mathcal{V}}_4(z, k_T, k_I; W) - c_f\},\end{aligned} \tag{12}$$

where the value of investing in both types of capital is given by

$$\begin{aligned}\tilde{\mathcal{V}}_1(z, k_T, k_I; W) &= \max_{k_T', k_I'} -x_T - x_I - \mathcal{C}(x_T, x_I; k_T, k_I) + \frac{1}{R}\int \mathcal{V}(z', k_T', k_I'; W)\Gamma(dz'|z), \\ &\text{s.t.} \quad k_T' = (1-\delta_T)k_T + x_T \quad \text{and} \quad k_I' = (1-\delta_I)k_I + x_I;\end{aligned} \tag{13}$$

the value of investing in only tangible capital is given by

$$\begin{aligned}\tilde{\mathcal{V}}_2(z, k_T, k_I; W) &= \max_{k_T'} -x_T - \mathcal{C}(x_T, 0; k_T, k_I) + \frac{1}{R}\int \mathcal{V}(z', k_T', (1-\delta_I)k_I; W)\Gamma(dz'|z), \\ &\text{s.t.} \quad k_p' = (1-\delta_T)k_T + x_T;\end{aligned} \tag{14}$$

the value of investing in only intangible capital is given by

$$\begin{aligned}\tilde{\mathcal{V}}_3(z, k_T, k_I; W) &= \max_{k_I'} -x_I - \mathcal{C}(0, x_I; k_T, k_I) + \frac{1}{R}\int \mathcal{V}(z', (1-\delta_T)k_T, k_I'; W)\Gamma(dz'|z), \\ &\text{s.t.} \quad k_i' = (1-\delta_I)k_I + x_I;\end{aligned} \tag{15}$$

and finally, the value of waiting is given by

$$\tilde{\mathcal{V}}_4(z, k_T, k_I; W) = \frac{1}{R}\int \mathcal{V}(z', (1-\delta_T)k_T, (1-\delta_I)k_I; W)\Gamma(dz'|z). \tag{16}$$

*Entrants problem.* The value of a potential entrant that draws initial productivity $s$, where

$s \sim \Lambda(s)$, is given by

$$\mathcal{V}_e(s; W) = \max_{k'_T, k'_I} -k'_T - k'_I + \frac{1}{R} \int \mathcal{V}(z', k'_T, k'_I; W)\Gamma(dz'|s). \tag{17}$$

Thus, the potential entrant will invest and start operating if and only if $\mathcal{V}_e(s; W) \geq c_e$.

## 4.2 Recursive Competitive Equilibrium

The *recursive competitive equilibrium* consists of (i) value functions $\mathcal{V}(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_1(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_2(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_3(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_4(z, k_T, k_I; W)$, and $\mathcal{V}_e(s; W)$; (ii) policy functions $\ell(z, k_T, k_I; W)$, $x_T(z, k_T, k_I; W)$, $x_I(z, k_T, k_I; W)$, $k'_T(s; W)$, and $k'_I(s; W)$; and (iii) an incumbent's measure $\Omega(z, k_T, k_I; W)$ and an entrant's measure $\mathcal{E}(z, k_T, k_I; W)$ such that:

1. $\mathcal{V}(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_1(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_2(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_3(z, k_T, k_I; W)$, $\tilde{\mathcal{V}}_4(z, k_T, k_I; W)$, $\ell(z, k_T, k_I; W)$, $x_T(z, k_T, k_I; W)$, and $x_I(z, k_T, k_I; W)$ solve (11), (12), (13), (14), (15), and (16);
2. $\mathcal{V}_e(s; W)$, $k'_T(s; W)$ and $k'_I(s; W)$ solve (17);
3. The labor market clears: $\int \ell(z, k_T, k_I; W) d\Omega(z, k_T, k_I; W) = L(W)$;
4. For all Borel sets $\mathcal{Z} \times \mathcal{K}_T \times \mathcal{K}_I \subset \mathbf{R}^+ \times \mathbf{R}^+ \times \mathbf{R}^+$,

$$\mathcal{E}(\mathcal{Z} \times \mathcal{K}_T \times \mathcal{K}_I; W) = m \int_{\mathcal{Z}} \int_{\mathcal{B}_e(\mathcal{K}_T, \mathcal{K}_I; W)} \Lambda(ds)\Gamma(dz'|s),$$

   where $\mathcal{B}_e(\mathcal{K}_T, \mathcal{K}_I; W) = \{z \text{ s.t. } k'_T(s; W) \in \mathcal{K}_T, k'_I(s; W) \in \mathcal{K}_I \text{ and } \mathcal{V}_e(s; W) \geq c_e\}$;
5. For all Borel sets $\mathcal{Z} \times \mathcal{K}_T \times \mathcal{K}_I \subset \mathbf{R}^+ \times \mathbf{R}^+ \times \mathbf{R}^+$ and $\forall t \geq 0$,

$$\Omega(\mathcal{Z} \times \mathcal{K}_T \times \mathcal{K}_I; W) = \int_{\mathcal{Z}} \int_{\mathcal{B}(\mathcal{K}_T, \mathcal{K}_I; W)} \Omega(dz, dk_T, dk_I; W)\Gamma(dz'|z) \quad + \quad \mathcal{E}(\mathcal{Z} \times \mathcal{K}_T \times \mathcal{K}_I; W),$$

   where $\mathcal{B}(\mathcal{K}_T, \mathcal{K}_I; W) = \{(z, k_T, k_I) \text{ s.t. } \max\{\tilde{\mathcal{V}}_1(z, k_T, k_I; W), \tilde{\mathcal{V}}_2(z, k_T, k_I; W), \tilde{\mathcal{V}}_3(z, k_T, k_I; W), \tilde{\mathcal{V}}_4(z, k_T, k_I; W)\} - c_f \geq \mathcal{V}_x(k_T, k_I), (1 - \delta_T)k_T + x_T(z, k_T, k_I; W) \in \mathcal{K}_T \text{ and } (1 - \delta_I)k_I + x_I(z, k_T, k_I; W) \in \mathcal{K}_I\}$.

## 4.3 Output Elasticities, Adjustment Costs, and $TFPR$ Dispersion

We follow Hopenhayn (2014) to define $TFPR$ as

$$\begin{aligned} TFPR_{ft} &= \frac{y_{ft}}{k_{T,ft}^{\alpha} k_{I,ft}^{\nu} \ell_{ft}^{(1-\alpha-\nu)}} \\ &\propto \left(\frac{MRPK_{T,ft}}{\alpha}\right)^{\alpha} \left(\frac{MRPK_{I,ft}}{\nu}\right)^{\nu} \left(\frac{MRPL_{ft}}{1-\nu-\alpha}\right)^{(1-\alpha-\nu)}, \end{aligned} \tag{18}$$

where $MRPK_{T,ft} = \alpha\, y_{ft}/k_{T,ft}$, $MRPK_{I,ft} = \nu\, y_{ft}/k_{I,ft}$, and $MRPL_{ft} = (1-\alpha-\nu)\, y_{ft}/\ell_{ft}$. Thus, $TFPR$ dispersion is then defined as

$$\begin{aligned} Var(\log TFPR_{ft}) = \alpha^2 Var\left(\log MRPK_{T,ft}\right) + \nu^2 Var\left(\log MRPK_{I,ft}\right) \\ + 2\alpha\nu Cov(\log MRPK_{T,ft}, \log MRPK_{I,ft}), \end{aligned} \tag{19}$$

where $Var(\cdot)$ is the variance and $Cov(\cdot)$ is the covariance. $TFPR$ dispersion in this economy is unaffected by $MRPL$, equalizing across firms due to labor's flexibility. Only $MRPK_T$ and $MRPK_I$ matter. Without adjustment costs, their marginal product equalizes, i.e., their variance is zero, yielding no $TFPR$ dispersion. With adjustment costs, capital reallocation slows, resulting in $Var\left(\log MRPK_{T,ft}\right)$ and $Var\left(\log MRPK_{I,ft}\right) > 0$, increasing $Var(\log TFPR_{ft}) > 0$. Equation (19) clarifies the relationship between intangible capital and $TFPR$ dispersion: an increase in its input share $\nu$ rises the importance of $Var\left(\log MRPK_{I,ft}\right)$, increasing overall $TFPR$ dispersion. This outcome arises from the shift away from undistorted inputs like labor to potentially distorted inputs like intangible capital. However, here $TFPR$ dispersion is not indicative of misallocation, as the economy remains constrained-efficient, similar to Asker, Collard-Wexler and De Loecker (2014).

## 4.4 Discussion About Modeling Choices

Online Appendix II.II.I demonstrates that our model is isomorphic to alternative interpretations of the role of intangible capital in firms' operations. In particular, it is isomorphic to a model in which intangible capital acts as a productivity shifter, as in Griliches (1979), where intangible capital investment represents an investment in productivity subject to adjustment costs. Alternatively, intangible capital can be viewed as a demand shifter that influences market demand without directly entering production. Under widely used assumptions, such as CES demand, this interpretation is also isomorphic to our model.

# 5 Model Calibration and Validation

## 5.1 Calibration

The model is calibrated for the 1980-1990 period, capturing the onset of US secular trends studied in the paper. The process involves two steps: first, fixing parameters estimated outside the model; second, choosing the remaining parameters to match key moments of the firms' investment distribution and life cycle.

*Fixed parameters.* Each model period corresponds to a year, so we set $R$ at 1.05. The annual depreciation rate for tangible capital, $\delta_T$, is 0.07. For intangible capital, we set the depreciation rate, $\delta_I$, at 0.29, the average observed in our data. Production function parameters are derived from our estimates. The returns to scale, $\omega$, are set at 0.90 (Hopenhayn and Rogerson, 1993; Khan and Thomas, 2008).[29] Idiosyncratic process persistence, $\rho_z$, is 0.89, and the standard deviation, $\sigma_z$, is 0.20 (Foster, Haltiwanger and Syverson, 2008; Lee and Mukoyama, 2015).

*Fitted parameters.* We determine the remaining parameters by matching moments from Table 1 and Business Dynamics Statistics (BDS). Positive spike rates identify fixed costs for tangible, $f_T$, and intangible capital investment, $f_I$, as they make firms willing to undertake only large investment projects (Cooper and Haltiwanger, 2006; Winberry, 2021). Serial correlation in investment rates identifies convex adjustment costs for both capital types, $\gamma_T$ and $\gamma_I$. Higher convex costs lead to slower capital stock adjustments and increased autocorrelation in firm-level investment (Cooper and Haltiwanger, 2006; Clementi and Palazzo, 2016a).[30] The entry cost, $c_e$, operating cost $c_f$, and the parameter governing the Pareto distribution of potential entrants' productivity, $\eta$, are calibrated to match the entry rate, the average size of incumbents, and the average size of entrants, respectively. Finally, the measure of potential

[29] In a competitive setting, obtaining a well-defined firm distribution requires decreasing returns to scale. Alternatively, the same can be achieved with unconstrained returns to scale and imperfect competition. With CES demand and elasticity of substitution $\sigma$, the revenue function's curvature is $\omega/\mu$, where $\mu = \sigma/(\sigma - 1)$; see Online Appendix II.II.II for details. Using $\omega = 1.1$ as estimated in Online Appendix I.III and a markup of 1.22 (close to the cost-weighted markup in De Loecker, Eeckhout and Unger, 2020), we obtain a curvature of the revenue function of 0.90, as in our calibration. Thus, under CES demand, our calibration is observationally equivalent to having increasing returns to scale in production and market power.

[30] Using the autocorrelation in investment downwardly biases convex costs in the presence of financial frictions (David and Venkateswaran, 2019). Thus, our convex costs should be interpreted as a lower bound.

entrants, $m$, is set to target an equilibrium wage of 1.

**Table 3: Parameters**

| Parameter | Value | Description |
|---|---|---|
| *Fixed* | | |
| $R$ | 1.05 | Annual interest rate |
| $\delta_T$ | 0.07 | Annual depreciation rate, tangible capital |
| $\delta_I$ | 0.29 | Annual depreciation rate, intangible capital |
| $\alpha$ | 0.28 | Tangible capital share |
| $\nu$ | 0.03 | Intangible capital share |
| $\omega$ | 0.90 | Returns to scale |
| $\rho_z$ | 0.89 | Autocorrelation idiosyncratic productivity |
| $\sigma_z$ | 0.20 | Standard deviation idiosyncratic productivity |
| *Fitted* | | |
| $\gamma_T$ | 0.058 | Convex adjustment cost $k_T$ |
| $\gamma_I$ | 0.700 | Convex adjustment cost $k_I$ |
| $f_T$ | 0.036 | Fixed adjustment cost $k_T$ |
| $f_I$ | 0.044 | Fixed adjustment cost $k_I$ |
| $c_e$ | 0.170 | Entry cost |
| $c_f$ | 1.780 | Operating cost |
| $\eta$ | 3.045 | Scale parameter |
| $m$ | 0.070 | Measure of potential entrants |

**Table 4: Empirical Targets**

| Target Moments | Model | Data |
|---|---|---|
| *Investment Rate Distributions* | | |
| Average investment rate $x_T$ | 0.16 | 0.11 |
| Average investment rate $x_I$ | 0.38 | 0.34 |
| corr $(x_{T,ft}, x_{T,ft-1})$ | 0.09 | 0.09 |
| corr $(x_{I,ft}, x_{I,ft-1})$ | 0.30 | 0.31 |
| Positive spike rate $x_T$ | 0.23 | 0.19 |
| Positive spike rate $x_I$ | 0.56 | 0.76 |
| *Firm Dynamics* | | |
| Entry rate | 0.13 | 0.13 |
| Average firm size | 20.1 | 20.5 |
| Average entrant size | 6.06 | 6.07 |
| Wage | 1.00 | — |

Note. The moments of the investment rate distributions are from Table 1. Data on firm entry rate, average firm size measured by the number of employees of a firm, and average entrant size from BDS.

Table 3 and 4 present the calibrated parameters and implied model moments. Despite the model's nonlinearity and over-identification (10 moments determining eight parameters), it successfully fits the targets in Table 4. As in Clementi and Palazzo (2019), our model indicates low fixed and convex costs for tangible capital, reflecting the predominance of large firms in the Compustat dataset. Additionally, it suggests higher adjustment costs for intangible capital, revealing that investment in intangibles faces greater technological frictions and is more distorted compared to a frictionless benchmark.

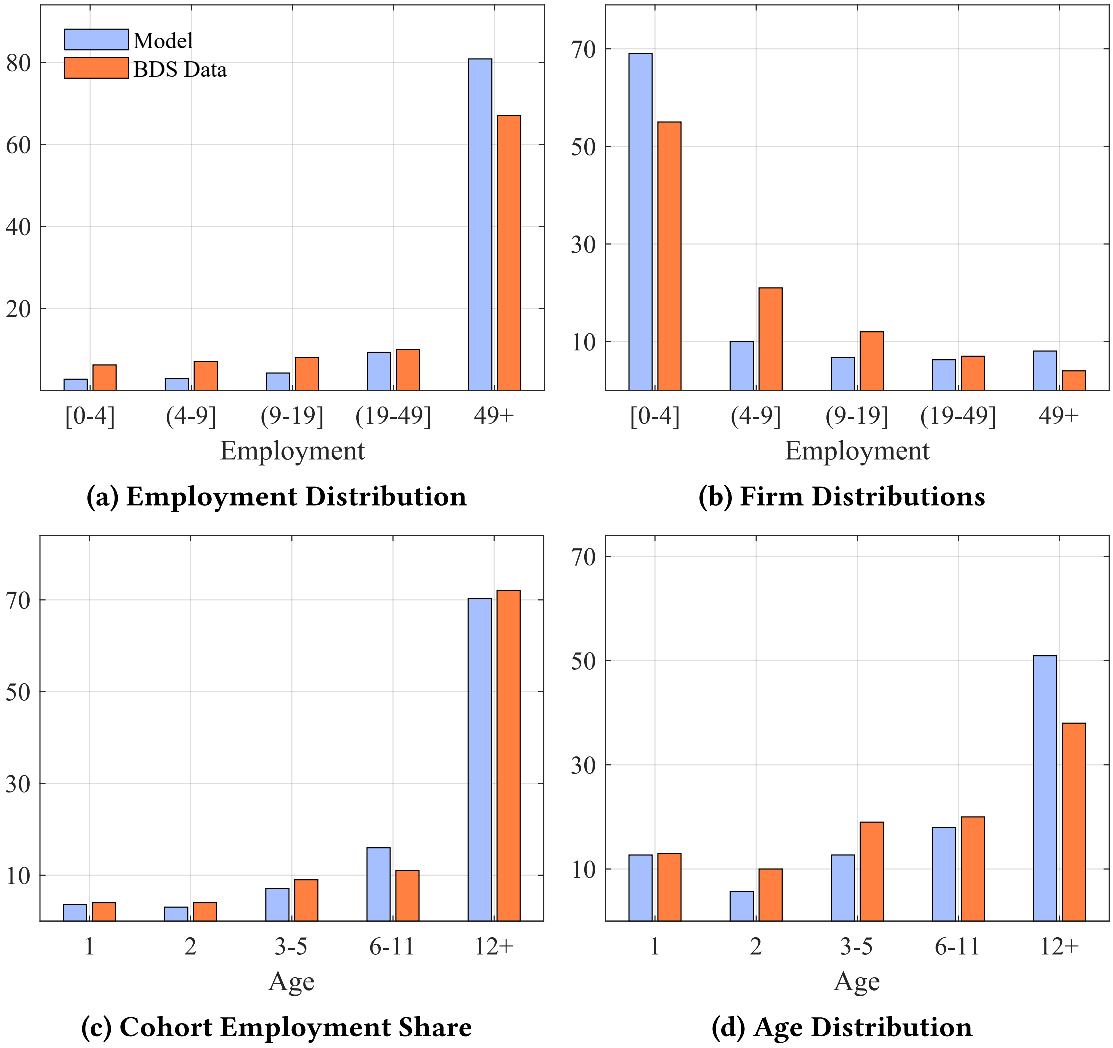
Our findings of high adjustment costs associated with intangible capital investments align with recent micro-level empirical evidence by Santoleri, Mina, Di Minin and Martelli (2024) and Bloesch and Weber (2022). The former found R&D investment responsive to subsidies, consistent with adjustment frictions, while the latter found that hiring new workers working with this capital creates congestion that leads to adjustment frictions. Additionally, our findings align with operational research case studies illustrating high adjustment frictions for investments like just-in-time production techniques and ERP systems (Nakamura, Sakakibara and Schroeder, 1998; Fullerton, McWatters and Fawson, 2003; Umble, Haft and Umble, 2003; Nicolaou, 2004; Galy and Sauceda, 2014). Finally, our findings support the notion of firm-specificity with underdeveloped secondary markets hindering intangible capital trade, as suggested by Akcigit, Celik and Greenwood (2016), Haskel and Westlake (2018), and David (2021).

Our parameterization is validated by the model's tangible capital to sales standard deviation equal to 2.30, close to the empirical 2.47, which identifies production process persistence (Clementi and Palazzo, 2016b). Also, the employment share for firms with 250+ employees is 0.49 in the model, closely aligning with the 0.51 in the data. Next, we further validate our calibration strategy by examining various non-targeted model implications.

## 5.2 Model Cross Section and Life Cycle Validation

Figure 6 compares model predictions about cross-sectional and life-cycle implications with empirical distributions from BDS. The model aligns well with the right-skewed size and age distributions. Regarding firm size, the model correctly generates that most firms in the economy are small and that few large firms account for the majority of employment (Figure 6a and 6b). For firm age, the model predicts similarly to the data that while only 40% of the firms are 11 years older, they account for more than 70% of total employment (Figure 6c and 6d).

Figure 6: Size and Age Distribution: Model vs. Data



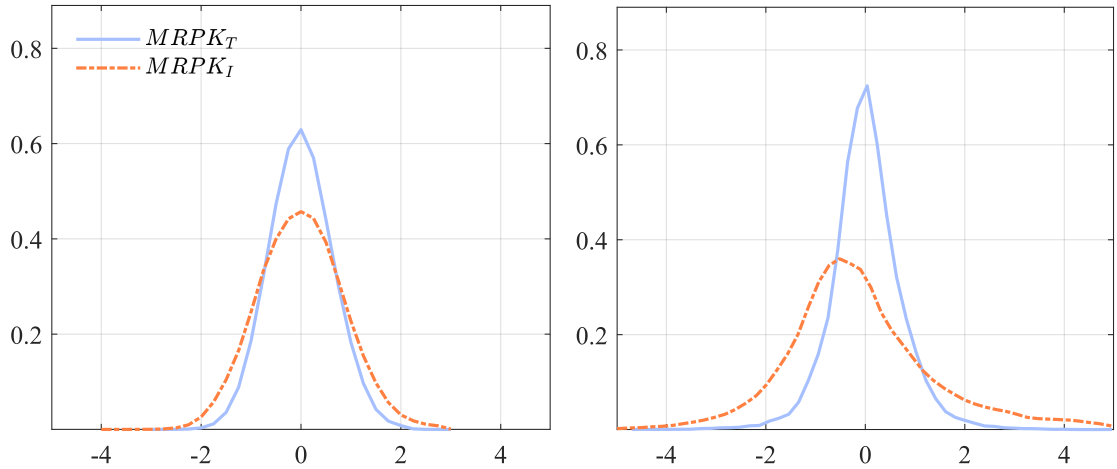

Note. The figures show the size (employment) and age distribution of the firms, in both the model and the data. Orange bars show the empirical distributions; light blue bars show the distributions from the model. The top left figure shows the employment share across different employment categories. The top right figure shows the share of firms across different employment categories. The bottom left figure shows the employment share across different age bins. The bottom right figure shows the share of firms across different age bins. Empirical distributions are from the BDS data.

## 5.3 Validation of Model Behavior of $MRPK_T$ and $MRPK_I$

Here, we validate the model-implied behavior of $MRPK_T$ and $MRPK_I$ looking at the relative dispersion and responsiveness to shocks of the marginal revenue product of both types of capital as documented empirically.

*Relative responsiveness.* Figure 7 illustrates the demeaned dispersion in the model (left) and the data (right). In both instances, the $MRPK_I$ exhibits greater dispersion compared to $MRPK_T$, stemming from higher adjustment frictions. While the model qualitatively reproduces this non-targeted difference, it does not fully capture it quantitatively, potentially indicating some role for additional frictions beyond adjustment costs affecting the $MRPK_I$.

**Figure 7: Marginal Revenue Product of Tangible and Intangible Capital: Model vs. Data**




**(a) Model** **(b) Data**

Note. Figure 7a shows the distribution of $MRPK_T$ (solid light blue line) and $MRPK_I$ (dashed orange line) from the model. Figure 7b shows the same distributions from the data. All distributions are demeaned.

*Relative responsiveness to shocks.* Table 5 displays estimates of equation (8) on both the model (columns 1-2) and the data (columns 3-4). Qualitatively, the model aligns well with the data, generating a higher coefficient for intangible capital due to its higher adjustment costs. Quantitatively, it reasonably matches the data without targeting them in the calibration, showing a 13% higher coefficient for intangible capital compared to the 26% in the data.

In conclusion, the model qualitatively matches various non-targeted moments related to the marginal revenue product of both capital types. It also reasonably aligns quantitatively. These results imply that adjustment costs alone go a long way in explaining the distinct behavior of the marginal revenue product of tangible and intangible capital.

# 6 IBTC Mechanism and Validation

## 6.1 Main Mechanism

Here, we examine the drivers behind the implications of IBTC. In the model, an increase in the output elasticity of intangible capital impacts (i) aggregate factor shares; (ii) average firm size, profit rate, and concentration; and (iii) TFPR dispersion. As a frictional input like

**Table 5: Heterogeneous Response of $MRPK_T$ and $MRPK_I$ to $TFPR$ Shocks: Model vs. Data**

| | Model | | Data | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable | $MRPK_T$ | $MRPK_I$ | $MRPK_T$ | $MRPK_I$ |
| $\varepsilon$ | 1.58*** | 1.78*** | 1.01*** | 1.27*** |
| | (0.00) | (0.00) | (0.00) | (0.01) |
| Time dummies | | | ✓ | ✓ |
| Firm dummies | | | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |

Notes. We report the coefficients from the regressions of $MRPK_T$ and $MRPK_I$ on revenue productivity shocks, $\varepsilon$. The controls include sales for columns 1 and 2 and sales, liquidity, and leverage for columns 3 and 4. The baseline specification is shown in equation (8). In the model, both marginal revenue products are at $t+1$ because of time to build. Standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

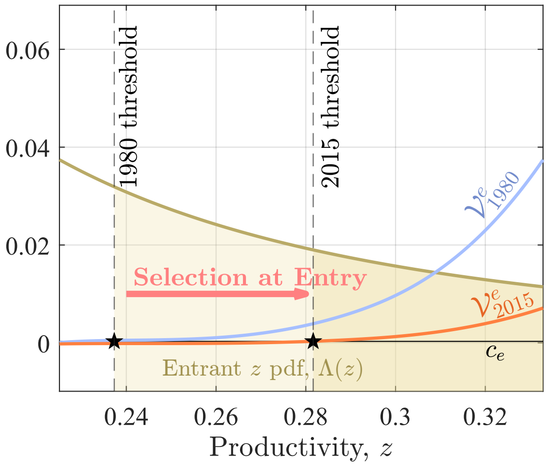
intangible capital rises, it influences the demand for each input, equilibrium wages, firms' selection and growth, and capital allocation across firms. This section aims to unveil these forces and establish their connection with IBTC.

Two key forces drive aggregate changes due to IBTC: (i) shifts in input demand resulting from firm-level technological change and (ii) endogenous change in the firm selection process due to the rise of a distorted input, i.e., intangible capital. Firstly, IBTC makes production more intangible-intensive, boosting demand for intangible capital while suppressing labor demand. This mechanically increases the intangible investment share and decreases the labor share.

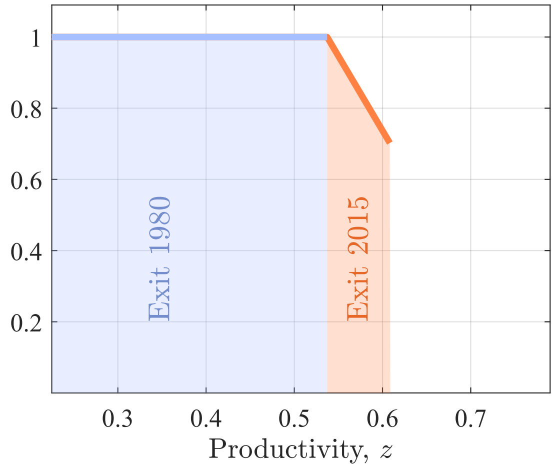
Secondly, firms respond to this technological shift by investing more in a distorted, high-adjustment-cost input like intangible capital. Only sufficiently productive firms can do this, impacting selection for both entrant and incumbent firms, as illustrated in Figure 8. Figure 8a shows that IBTC diminishes the attractiveness of entry ($\mathcal{V}^e_{1980} > \mathcal{V}^e_{2015}$). This shifts the entry threshold rightward, indicating that by 2015 (post-IBTC), only more productive firms can afford to enter. Similarly, Figure 8b reveals a parallel increase in selection for incumbent firms. In the post-IBTC economy, marginally more productive firms face a positive exit probability, showing that IBTC heightens both ex-ante and ex-post selection in the economy.

Despite IBTC mechanically boosting intangible capital demand, it does not proportionately raise the aggregate intangible investment share. This is due to changes in selection favoring more productive firms, who, anticipating future contraction due to productivity mean

**Figure 8: IBTC and Firms' Selection**




**(a) Entry Decision**




**(b) Exit Probability**

Note. Figure 8a shows graphically the entry problem of potential entrants in both the 1980 and 2015 calibrations. The 2015 calibration is shown in Section 7. The beige line in the background shows the productivity distribution of potential entrants, $\Lambda(z)$. The light blue and orange curves show the value function of potential entrants for both calibrations, $\mathcal{V}^e_{1980}$ and $\mathcal{V}^e_{2015}$. The value of entry is lower in 2015 compared to 1980 because in order to grow in the intangible-intensive economy, firms have to spend more resources on high adjustment costs. The black line shows the entry cost, $c_e$. The two vertical dashed black lines show the exit threshold in both 1980 and 2015, that is, the productivity level that satisfies $c_e = \mathcal{V}^e_t(z),\ t \in \{1980, 2015\}$. The shaded light beige area in the background shows the ex-post productivity distribution of entrants in 1980, and the shaded dark beige area in the background shows the ex-post productivity distribution of entrants in 2015. Figure 8b shows the exit probability of incumbent firms for both the 1980 and 2015 calibrations. The light blue line shows the exit probability for incumbent firms in 1980. The orange line shows the exit probability in 2015. Firms with higher productivity in 2015 face a positive probability of exit because, in the intangible-intensive economy, it is more difficult to operate as they have to spend more on adjustment costs in order to respond to productivity shocks.

reversion, exhibit lower investment rates. Consequently, the rise in aggregate intangible capital share is dampened. This same mechanism, not compensated by a rise in input share as for intangible capital, drives the decline in aggregate tangible investment share. Finally, the labor share declines solely due to the change in firm-level input share, with no impact from the change in selection.

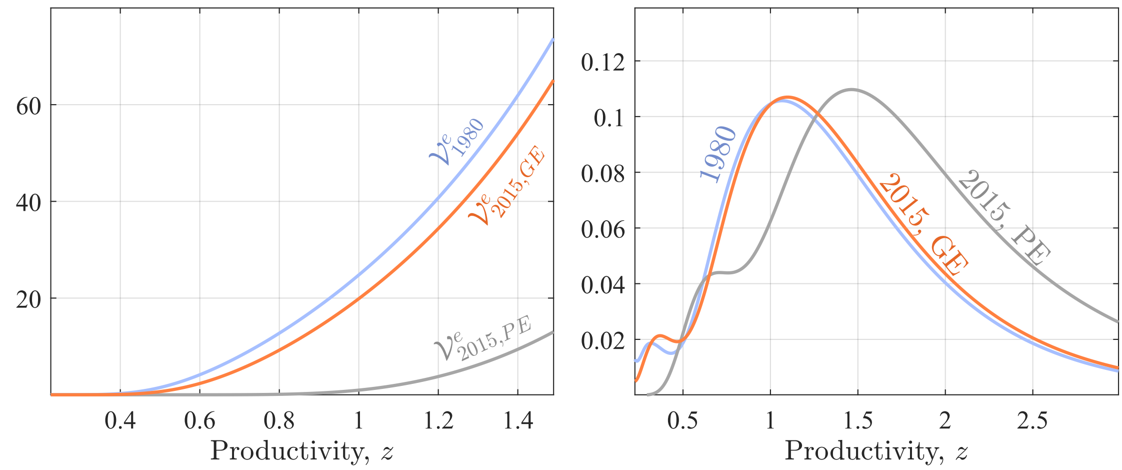
Moreover, IBTC increases average firm size, profit rate, and concentration through a change in selection and by favoring larger firms. Small firms face higher adjustment costs hindering their growth, while large firms can more easily shrink due to the high depreciation rate of intangible capital. This, along with higher selection allowing the operations of more productive firms only, results in a redistribution of sales shares toward larger firms, increasing the average firm size, profit rate, and industry concentration.

Finally, as the intangible capital share rises, the model predicts a rise in $TFPR$ dispersion. In the model, $TFPR$ dispersion is given by equation (19). When the output elasticity of intangible capital increases, the contribution of $MRPK_I$ dispersion to $TFPR$ dispersion increases, resulting in its overall rise in the model.

## 6.2 General vs. Partial Equilibrium

We analyze the consequences of IBTC on the economy, distinguishing between partial and general equilibrium effects. Solving for the 2015 post-IBTC economy while keeping wages constant captures only partial equilibrium effects. In this context, the post-IBTC value of entry ($\mathcal{V}^e_{2015,PE}$) substantially drops compared to the pre-IBTC ($\mathcal{V}^e_{1980}$), raising the productivity of the marginal entrant (Figure 9a). A similar increase in selection occurs for exiting firms, causing a rightward shift in the distribution of incumbent firms (Figure 9b).

**Figure 9: General vs. Partial Equilibrium effects**




**(a) Entrant Value Function** **(b) Incumbents Distribution**

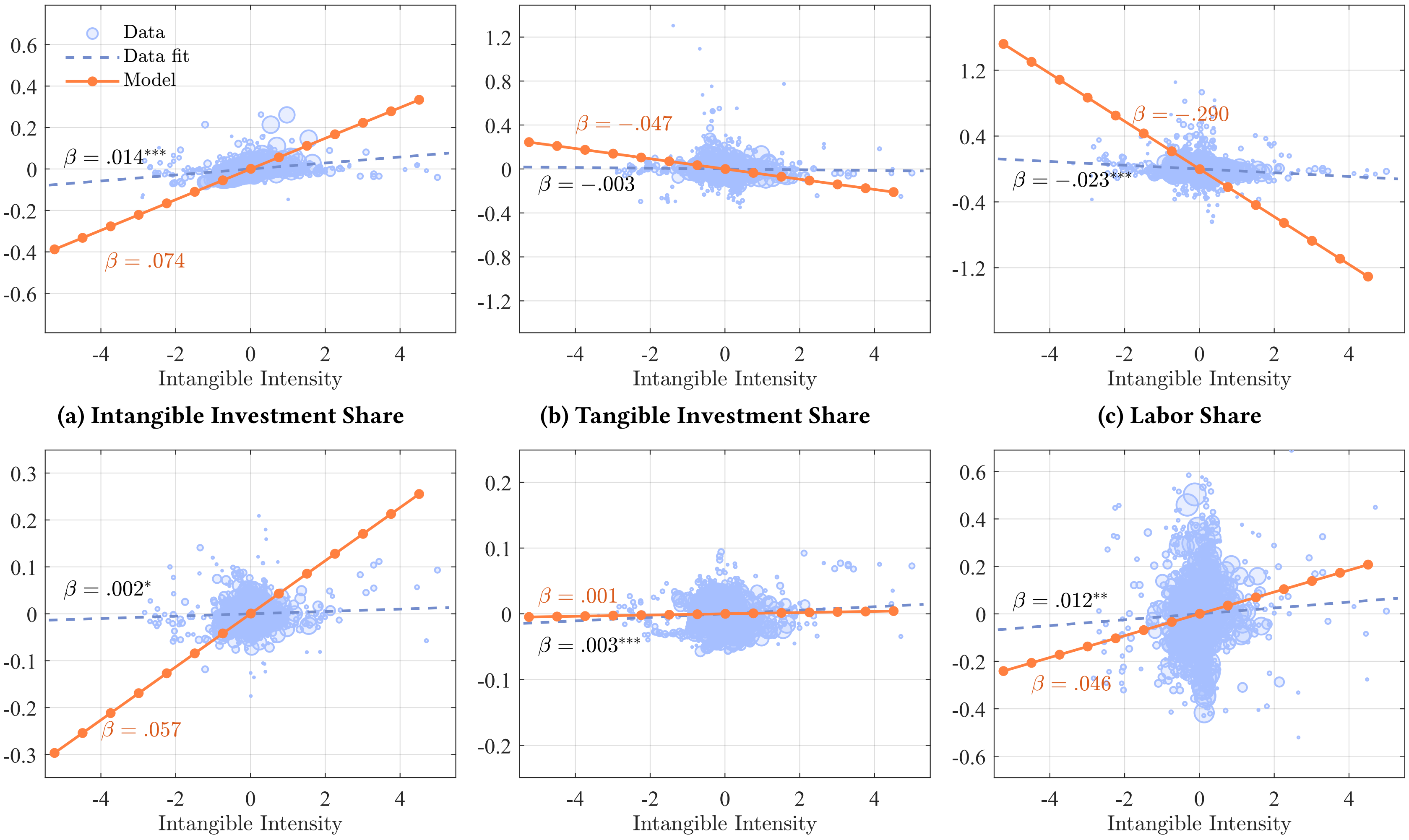
Note. Figure 9a shows the value of entry in 1980 and 2015 for both the general equilibrium version of the model and the partial equilibrium one. The light blue line shows the value of entry in 1980, the orange line shows the value of entry in 2015-GE, and the light gray line shows the value of entry in 2015-PE. The value of entry declines between 1980 and 2015 because in order to grow in the intangible-intensive economy, firms have to spend more resources on high adjustment costs. The value of entry declines more in PE relative to GE because in general equilibrium, the wage declines and acts like a dampening force on the effect of IBTC. Figure 9b shows the endogenous distribution of firms in the economy in 1980 and 2015 for both the general equilibrium version of the model and the partial equilibrium one. The light blue line shows the distribution in 1980, the orange line shows the distribution in 2015-GE, and the light gray line shows the distribution in 2015-PE. The distribution shifts to the right because of the increase in selection mentioned above. Again, the decline in wages dampens the PE effect, resulting in a milder shift of the GE distribution toward the right.

When wages adjust endogenously, the general equilibrium value of entry ($\mathcal{V}^e_{2015,GE}$) declines substantially less compared to the partial equilibrium ($\mathcal{V}^e_{2015,PE}$). This lower decline results from a wage decline caused by reduced firm entry lowered output elasticity of labor at the firm level, and increased overall adjustment costs. This wage decline acts as a counterbalancing force to the partial equilibrium selection effect of IBTC. This exercise underscores the importance of general equilibrium effects in accurately assessing the macroeconomic implications of IBTC, preventing an overestimation of its role in explaining recent trends.

### 6.3 Cross-Sectoral Validation of the Mechanism

Here we validate the mechanisms outlined above by examining how varying intangible capital shares, $\nu$, influence sector-level factor shares, concentration, and $TFPR$ dispersion. Given the challenges in precisely measuring intangible capital shares in production at the sector level, in the data we employ a directly observable proxy directly linked to changes in $\nu$: intangible intensity, defined as the ratio of intangible capital to labor cost. To capture the same variation, in the model, we look at the following: $\beta \equiv (\partial \text{Outcome}/\partial \nu)/(\partial \text{Intangible intensity}/\partial \nu)$.

**Figure 10: Sector-Level Correlations: Model vs. Data**




**(a) Intangible Investment Share** **(b) Tangible Investment Share** **(c) Labor Share**

**(d) Profit Rate** **(e) Concentration (HHI)** **(f) TFPR Dispersion**

Note. The figure shows the cross-sectoral correlations between intangible intensity, $k_I/w\ell$, and various measures of interest. Light blue bubbles show the sector-year observations net of the sector- and time-fixed effects. Sectors are defined at the SIC2 level. The dashed light blue lines show the empirical fit. The solid orange lines with circles show the model-implied slope.

Figure 10 compares model predictions (orange lines with circles) to data fits (dashed light blue lines) for key sector-level metrics: (i) intangible investment share, (ii) tangible investment share, (iii) labor share, (iv) profit rate, (v) concentration, and (vi) TFPR dispersion. The figure shows consistent support for all qualitative model predictions across various sectors.

# 7 IBTC and the Macroeconomy

This section quantifies and discusses the implications of IBTC.

## 7.1 Quantitative Implications

Here we study the quantitative implications of IBTC. To this end, we assess its impact through two scenarios: (i) "Baseline IBTC" scenario referring to the estimates from Section 3.1, in which the firm-level intangible capital share increases by 7 percentage points at the expense of labor; and (ii) a "Conservative IBTC" scenario referring to the *most* conservative estimates from our robustness checks coming from the sector-level production function estimation — aggregated with the corresponding sector share—provided in Online Appendix I.III.III, where the firm-level intangible capital share increases by 5 percentage points at the expense of labor. Table 6 presents the results.[31]

**Firms' distribution.** Examining firm-level outcomes, IBTC is consistent the observed growth in average firm size, slightly overpredicting its extent in both scenarios. Similarly, it accounts for the increase in concentration, measured by the HHI, and the employment share of firms with 250+ employees. These outcomes result from the increase in selection and the reallocation of economic activities toward larger firms, as explained in Section 6.

**Aggregate factor shares.** Comparing the implications of IBTC with Koh, Santaeulàlia-Llopis and Zheng (2020) findings on factor shares in the non-financial corporate sector, the model captures quantitatively much of them. It accounts for 50-75% of the increase in the aggregate intangible investment share, even though the micro-level rise is 7 p.p. compared to a 2-3 p.p. increase in the aggregate. This underscores the significance of micro-level frictions, like adjustment costs, in matching quantitatively aggregate trends. Without adjustment costs, the aggregate increase would align more closely with the micro-level rise, emphasizing the

[31] In Online Appendix II.III, we document the evolution between 1980-2015 of the distribution of intangible intensity and TFPR in both the model and the data.

**Table 6: Quantitative Implications of IBTC**

| | Model | | |
|---|---|---|---|
| | Baseline IBTC | Conservative IBTC | Data |
| *Firm Distribution* | | | |
| Avg. firm size | $+27\%$ | $+19\%$ | $+15\%$ |
| Concentration | $+39\%$ | $+33\%$ | $+33\%$ |
| Employment share | | | |
| firms with 250+ employees | +3p.p. | +5p.p. | +6p.p. |
| *Aggregate Factor Shares* | | | |
| Intangible investment share | +3p.p. | +2p.p. | +4p.p. |
| Tangible investment share | −3p.p. | −2p.p. | −2p.p. |
| Labor share | −7p.p. | −5p.p. | −8p.p. |
| Labor share pre-revision | −5p.p. | −4p.p. | −5p.p. |
| Profit rate | +7p.p. | +5p.p. | +6p.p. |
| *Aggregate Investment Rate* | | | |
| Tangible investment rate | −2p.p. | −2p.p. | −2p.p. |
| *Aggregate Productivity* | | | |
| sd($TFPR$) | $+6\%$ | $+3\%$ | $+38\%$ |
| Adjusted sd($TFPR$) | $+6\%$ | $+3\%$ | $+15\%$ |
| Aggregate productivity | $-1\%$ | $-1\%$ | |

Note. All variables are computed according to their definitions as used in the data. "Baseline IBTC" refers to the estimates from Section 3.1, in which the firm-level intangible capital share increases by 7 percentage points at the expense of labor. "Conservative IBTC" refers to the sector-level estimates—aggregated with the corresponding sector share—provided in Online Appendix I.III.III, where the firm-level intangible capital share increases by 5 percentage points at the expense of labor. Data sources include BDS, NIPA tables, and Compustat. To calculate the empirical moments for the 1980s, we use the time window 1980–1990, whereas for the 2015 empirical moments, we use the values from that year.

moderating effect of adjustment costs on overall investment growth in the second steady state.

To study the impact of IBTC on the decline in the labor share, we follow Koh, Santaeulàlia-Llopis and Zheng (2020)'s approach by computing two labor shares in the model:

$$LS = \frac{WL}{Y} \quad \text{and} \quad LS_{\text{pre-revision}} = \frac{WL}{Y - X_I}.$$

Here, $W$ is the wage, $L$ is aggregate labor, $Y$ is aggregate output net of adjustment and fixed costs, and $X_I$ is aggregate intangible investment. In the pre-revision period, intangible capital was ignored as a component of aggregate GDP, whereas in the post-revision period—used by the BEA today—it is fully recognized. The pre-revision labor share, which excludes intangible capital from GDP, declines less than the true labor share, in line with Koh, Santaeulàlia-Llopis and Zheng (2020)'s findings. This demonstrates that our model, by treating intangible capital as a fully dynamic input whose investment is part of GDP, not only replicates between 62-87% of the observed decline in the labor share but also correctly attributes a quantitatively major role to rising intangible capital investment in its decline.

The model effectively captures the decline in the tangible investment share, driven both by increased selection—which shifts the distribution toward older, lower-investment firms—and by the rise in intangible investment, which increases the denominator of this ratio. Finally, the model is also quantitative in line with the rise in the profit rate, partly through increased selection and reallocation toward larger firms, as explained in Section 6.

**Aggregate productivity.** IBTC accounts for the economy's rise in $TFPR$ dispersion. Slower input reallocation towards more productive firms when relying more on a highly frictional input like intangible capital compared to a flexible input like labor worsens overall resource allocation, as reflected by the rising TFPR standard deviation. Importantly, this should not be deemed as misallocation, as the economy is fully efficient and the resource allocation aligns with the social planner. In summary, the model captures between 20-40% of the quantitative rise in adjusted $TFPR$ dispersion.[32]

Finally, our model predicts an approximate 1% decline in aggregate productivity, resulting from several countervailing forces. On one hand, stronger selection raises average firm productivity. On the other hand, the shift toward intangible capital—characterized by high adjustment costs—has two negative effects. First, since these adjustment costs are paid in output, a larger share of output is consumed by them, reducing productivity. Second, a higher reliance on an input with elevated adjustment costs weakens the correlation between firm size and productivity, further lowering aggregate productivity. Although the decline in TFP growth has been extensively documented, directly mapping our model's findings is challenging because our framework implies a decline in TFP levels. Nonetheless, the model remains consistent with the overall evolution of US productivity.

## 7.2 Robustness Checks

In this section, we conduct a series of robustness checks around our baseline IBTC scenario: (i) restricting to convex adjustment costs; (ii) identifying fixed adjustment costs using inaction

[32] Adjusted $TFPR$ dispersion is measured as $TFPR$ dispersion net of a 60% measurement error, as documented by Bils, Klenow and Ruane (2021), i.e., $(1 - 0.60) \times 38\% = 15\%$.

rates rather than spike rates; (iii) recalibrating 2015 steady-state adjustment costs to match the moments of the investment-rate distribution; (iv) allowing the relative price of intangible capital to decline in the 2015 steady state, as observed in the data, under a Cobb–Douglas production function; (v) endogenizing tangible and intangible capital prices under a Cobb–Douglas production function; (vi) allowing the relative price of intangible capital to decline in the 2015 steady state, as observed in the data, under a CES production function; (vii) allowing both a decline in the relative price of intangible capital in the 2015 steady state and changes in input shares, as observed in the data, under a CES production function; and (viii) endogenizing tangible and intangible capital prices while allowing input shares to change, as observed in the data, under a CES production function.

In the first robustness test (Column 2, CD, Convex Costs Only), we eliminate fixed adjustment costs and recalibrate. Results in Table 7 closely track the benchmark, indicating that the key margin is not non-convexities per se but the asymmetry in adjustment costs across investment types. Detailed parameters and moments are reported in the Online Appendix II.III..

In the second test (Column 3, CD, Matching Inaction Rates), we identify fixed adjustment costs using inaction rates instead of spike rates. As shown in Table 7, the results remain close to the benchmark and the calibration continues to recover higher fixed costs for intangible investment. See Online Appendix II.III. for parameters and moments.

In the third test (Column 4, CD, Alternative Adjustment Costs), we recalibrate all adjustment-cost parameters in the post-IBTC steady state to match the 2015 investment-rate distribution. Table 7 shows results very similar to the benchmark. Recalibration does not yield materially different parameters over time, suggesting their structural stability.

In the fourth test (Column 5, CD, Decline in Relative Price $k_I$), we feed a 50% decline in the relative price of intangible capital from 1980 to 2015 into the model by adjusting the value functions (13)–(17). The findings remain consistent with the benchmark, indicating only a modest role for the observed price decline.

In the fifth test (Column 6, CD, Endogenous Capital Prices), we fix the aggregate quantities of tangible and intangible capital at their 1980 levels and allow their prices to adjust in general equilibrium to the 2015 IBTC environment. Table 7 again aligns with the benchmark, implying that these general-equilibrium price adjustments play a limited role for our main results.

## Table 7: Quantitative Implications of IBTC: Robustness and CES–II Counterfactuals

| | Change | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CD Benchmark | CD Convex Costs Only | CD Matching Inaction Rates | CD Alternative Adj. Costs | CD Decline Rel. Price $k_I$ | CD Endogenous Capital Prices | CES Decline Rel. Price $k_I$ | CES Decline Rel. Price $k_I$ $\Delta$ Input weights | CES Endogenous Capital Prices $\Delta$ Input weights | Data |
| *Firm Distribution* | | | | | | | | | | |
| Avg. firm size | +27% | +26% | +24% | +17% | +29% | +26% | −5% | −25% | −9% | +15% |
| Concentration ($HHI$) | +39% | +42% | +42% | +39% | +39% | +27% | −11% | −48% | −12% | +33% |
| Employment share firms with 250+ employees | +3p.p. | +4p.p. | +4p.p. | +3p.p. | +5p.p. | +4p.p. | +0p.p. | −5p.p. | −4p.p. | +6p.p. |
| *Aggregate Factor Shares* | | | | | | | | | | |
| Intangible investment share | +4p.p. | +3p.p. | +3p.p. | +3p.p. | +3p.p. | +3p.p. | +1p.p. | +4p.p. | +1p.p. | +4p.p. |
| Tangible investment share | −3p.p. | −2p.p. | −3p.p. | −2p.p. | −3p.p. | −3p.p. | −1p.p. | +1p.p. | +1p.p. | −2p.p. |
| Labor share | −7p.p. | −7p.p. | −7p.p. | −7p.p. | −7p.p. | −7p.p. | −1p.p. | −5p.p. | −2p.p. | −8p.p. |
| Labor share (pre-revision) | −5p.p. | −5p.p. | −5p.p. | −5p.p. | −4p.p. | −5p.p. | −1p.p. | −2p.p. | −2p.p. | −5p.p. |
| Profit rate (Compustat) | +7p.p. | +6p.p. | +6p.p. | +6p.p. | +7p.p. | +6p.p. | +1p.p. | +0p.p. | −1p.p. | +3p.p. |
| Profit rate (BEA) | +7p.p. | +6p.p. | +6p.p. | +6p.p. | +7p.p. | +6p.p. | +1p.p. | +0p.p. | −1p.p. | +5p.p. |
| *Aggregate Investment Rate* | | | | | | | | | | |
| Tangible investment rate | −2p.p. | −1p.p. | −1p.p. | −1p.p. | −2p.p. | −2p.p. | −0p.p. | +0p.p. | −0p.p. | −2p.p. |
| *Allocative Efficiency* | | | | | | | | | | |
| sd($TFPR$) | +6% | +7% | +7% | +7% | +6% | +7% | +4% | +14% | +2% | +38% |
| Adjusted sd($TFPR$) | +6% | +7% | +7% | +7% | +6% | +7% | +4% | +14% | +2% | +15% |

Note. Column 1 (CD, Benchmark) reports results from the main specification. Column 2 (CD, Convex Costs Only) reports results from a calibration that permits only convex adjustment costs (no fixed adjustment costs). Column 3 (CD, Matching Inaction Rates) reports results from a calibration in which fixed adjustment costs are identified using inaction rates rather than spike rates. Column 4 (CD, Alternative Adjustment Costs) reports results from recalibrating the model to match investment-rate moments in 2015. Column 5 (CD, Decline in Relative Price $k_I$) reports results when the relative price of intangible capital is reduced in the 2015 steady state under a Cobb–Douglas production function, consistent with data over the same period. Column 6 (CD, Endogenous Capital Prices) reports results when the aggregate quantities of tangible and intangible capital are fixed at 1980 levels, allowing prices to adjust in general equilibrium after IBTC. Column 7 (CES, Decline in Relative Price $k_I$) reports the CES counterfactual with a decline in intangible prices only. Column 8 (CES, Decline in Relative Price $k_I$, $\Delta$ input weights) reports the CES counterfactual with a decline in intangible prices and rising importance of intangibles via $\Delta$ input weights. Column 9 (CES, Endogenous Capital Prices, $\Delta$ input weights) reports the CES counterfactual with endogenous capital prices and rising importance of intangibles via $\Delta$ input weights. Column 10 (Data) reports empirical moments from Compustat and the BDS.

For the sixth through eighth tests we replace the Cobb–Douglas production function with a CES specification following Aum and Shin (2024). The elasticity of substitution is 0.4 between tangible capital and labor and 2.5 between the tangible-capital–labor bundle and intangible capital; the economy is recalibrated to match 1980 moments (see Online Appendix II.III). We also introduce in the model the relative price of both capitals by adjusting the value functions (13)–(17) accordingly.

In the sixth CES test (Column 7, CES, Decline in Relative Price $k_I$), we feed a 50% decline in the relative price of intangible capital from 1980 to 2015. Table 7 shows weaker quantitative fit relative to the benchmark, indicating that substitution between intangible capital and the tangible-capital–labor bundle—especially under strong adjustment costs—is not sufficient to account for the observed rise in intangible investment. This points to an additional technology channel associated with IBTC, beyond price changes and substitutability.

To see this point, in the seventh CES test (Column 8, CES, Decline in Relative Price $k_I$, $\Delta$ input weights), we combine the 50% price decline with a 7 p.p. increase in the weight on intangible capital,offset by an equal decline in the weight on labor, consistent with the data (see Online Appendix II.III). As shown in Table 7, the model's fit improves, particularly for changes in aggregate intangible investment and the labor share, relative to the price-only counterfactual.

In the eighth CES test (Column 9, CES, Endogenous Capital Prices, $\Delta$ input weights), we hold aggregate quantities fixed at 1980 levels, allow prices to adjust endogenously, and again raise the intangible weight by 7 p.p. Consistent with expectations, the rising importance of intangible capital coupled with fixed aggregate quantities leads to a pronounced increase in its relative price, dampening the rise in the intangible investment share and reducing the model's quantitative fit.

## 7.3 IBTC, Complementary Explanations, and Policy Implications

As production technology leans towards intangible capital, firms invest more in a high adjustment cost input. This shift increases concentration, firm size, and the aggregate profit rate without compromising resource allocation efficiency. The rise in $TFPR$ dispersion and the decline in aggregate productivity are attributed to technological constraints, and the decentralized equilibrium aligns with the social planner's allocation. Our findings propose a more benign interpretation of this trends as they show that a substantial part of macroeconomic trends in the US can be the by-product of an efficient technological change.

This conclusion does not rule out the presence of additional complementary factors, such as the rise in market power (De Loecker, Eeckhout and Unger, 2020), demographic changes (Karahan, Pugsley and Şahin, 2024), or offshoring (Elsby, Hobijn and Şahin, 2013), operating in the economy. IBTC, increased market power, slowdown in labor force growth, and rising offshoring can coexist and complement each other, explaining quantitative margins that IBTC alone cannot fully account for. For instance, while IBTC goes a long way toward explaining the evolution of the distribution of firms and aggregate factor shares—even though it does not capture all aspects of these trends, particularly under more conservative scenario—it falls short in accounting for the observed changes in business dynamism.

To illustrate this, we calculate several statistics related to business dynamism, including the mass of incumbent and entrant firms, the entry rate,[33] and the reallocation rate. In the baseline scenatio the model predicts a substantial decline in the mass of operating firms and new entrants, a 3 percentage point increase in the entry rate, and a 2 percentage point decline in the reallocation rate. The mass of entrants declines substantially due to increased selection at entry, while greater selection at exit—driven by higher adjustment costs associated with intangible capital that make it difficult for less productive firms to operate—further reduces the total number of operating firms. However, we find that the decline in entrants is smaller than the overall decline in firms, thus the entry rate in the new steady state is slightly higher than in 1980. Meanwhile, the reallocation rate in the 2015 steady state is slightly lower than in 1980. Thus, although the implications of IBTC align with anecdotal evidence that US markets are increasingly dominated by a few large firms—Grullon, Larkin and Michaely (2019) show that the number of firms in various Compustat sectors has declined, increasing concentration, and Deb, Eeckhout, Patel and Warren (2022) demonstrate that a model-implied measure of operating firms has fallen substantially—this evidence is typically associated with a joint decline in entry and reallocation rates.

Thus, we conclude that IBTC alone is unlikely to be the major driver behind the decline in business dynamism, and that complementary forces must have contributed to the overall developments in the US economy since the 1980s. These forces could include the rise in market power and its interplay with increasing sunk costs—as highlighted in this paper—in a manner

[33]We report only the entry rate since in a stationary equilibrium it equals the exit rate.

similar to De Loecker, Eeckhout and Unger (2020) and De Loecker, Eeckhout and Mongey (2021)—, the slowdown in labor force growth, as emphasized in Karahan, Pugsley and Şahin (2024) and Hopenhayn, Neira and Singhania (2022), or the rise in offshoring as discussed in Elsby, Hobijn and Şahin (2013). Although all these forces have demonstrated substantial quantitative explanatory power for the decline in business dynamism, their analyses have typically been conducted in isolation—a point noted by Grossman and Oberfield (2022)—and thus the interplay between them, as well as with IBTC, remains unexplored.

We conclude by emphasizing that even if complementary forces coexisting with IBTC lead to a decentralized allocation that deviates from the social planner's optimum, any policy designed to implement the social planner's allocation would still operate within the efficient mechanism outlined in this paper. Thus, while the broader literature does not rule out policy interventions to counteract inefficient complementary forces, our main finding suggests that a significant portion of the observed macroeconomic trends in the US may be the byproduct of the economy's efficient response to changes in firm-level production technology—trends that may not be counteracted through policy measures without harming overall welfare.

# 8 Conclusion

This paper contributes to understanding intangible capital and its role in reconciling macro trends observed in the US economy. Our estimation of firm-level production functions reveals the increasing significance of intangible capital at the expense of labor, with its input share rising from 0.03 in the 1980s to 0.10 in 2015. We term this technological change IBTC. Additionally, we uncover distinctive properties of intangible capital, notably higher adjustment costs compared to tangible capital. Using a quantitative model, we quantify the implications of IBTC, demonstrating its capacity to explain a substantial fraction of many US secular trends, including increased firm size and concentration, changes in factor shares, rise in $TFPR$ dispersion and decline in aggregate productivity. Our findings suggest that a substantial fraction of these transformations can be attributed to the efficient response of the economy to changes in firm-level production technology.

# References

**Abel, Andrew B and Janice C Eberly**, "A unified model of investment under uncertainty," *American Economic Review*, 1994, *84*, 1369–1384.

— **and** — , "Optimal investment with costly reversibility," *The Review of Economic Studies*, 1996, *63* (4), 581–593.

**Acemoglu, Daron, Gary Anderson, David Beede, Catherine Buffington, Eric Childress, Emin Dinlersoz, Lucia Foster, Nathan Goldschlag, John Haltiwanger, Zachary Kroff et al.**, "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey," 2022.

**Ackerberg, Daniel A, Kevin Caves, and Garth Frazer**, "Identification properties of recent production function estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

**Aghion, Philippe, Antonin Bergeaud, Timo Boppart, Peter J Klenow, and Huiyu Li**, "A theory of falling growth and rising rents," *Review of Economic Studies*, 2023, *90* (6), 2675–2702.

**Akcigit, Ufuk and Sina T Ates**, "Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory," *American Economic Journal: Macroeconomics*, 2021, *13* (1), 257–98.

— **and** — , "What happened to US business dynamism?," *Journal of Political Economy*, 2023, *131* (8), 2059–2124.

— **, Murat Alp Celik, and Jeremy Greenwood**, "Buy, keep, or sell: Economic growth and the market for ideas," *Econometrica*, 2016, *84* (3), 943–984.

**Alexander, Lewis and Janice Eberly**, "Investment hollowing out," *IMF Economic Review*, 2018, *66*, 5–30.

**Altomonte, Carlo, Domenico Favoino, Monica Morlacco, and Tommaso Sonno**, "Markups, intangible capital and heterogeneous financial frictions," Technical Report, Centre for Economic Performance, LSE 2021.

**Asker, John, Allan Collard-Wexler, and Jan De Loecker**, "Dynamic inputs and resource (mis) allocation," *Journal of Political Economy*, 2014, *122* (5), 1013–1063.

**Atkeson, Andrew**, "Alternative facts regarding the labor share," *Review of Economic Dynamics*, 2020, *37*, S167–S180.

— **and Patrick J Kehoe**, "Modeling and measuring organization capital," *Journal of political Economy*, 2005, *113* (5), 1026–1053.

**Aum, Sangmin and Yongseok Shin**, "Is Software Eating the World?," Technical Report, National Bureau of Economic Research 2024.

**Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen**, "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

**Barkai, Simcha**, "Declining labor and capital shares," *The Journal of Finance*, 2020, *75* (5), 2421–2463.

**Bates, Thomas W, Kathleen M Kahle, and René M Stulz**, "Why do US firms hold so much more cash than they used to?," *The journal of finance*, 2009, *64* (5), 1985–2021.

**Belo, Frederico, Vito D Gala, Juliana Salomao, and Maria Ana Vitorino**, "Decomposing firm value," *Journal of Financial Economics*, 2022, *143* (2), 619–639.

**Bhandari, Anmol and Ellen R McGrattan**, "Sweat equity in US private business," *The Quarterly Journal of Economics*, 2021, *136* (2), 727–781.

**Bils, Mark, Peter J Klenow, and Cian Ruane**, "Misallocation or mismeasurement?," *Journal of Monetary Economics*, 2021, *124*, S39–S56.

**Bloesch, Justin and Jacob P Weber**, "Congestion in Onboarding Workers and Sticky R&D," 2022.

**Brown, James R, Steven M Fazzari, and Bruce C Petersen**, "Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom," *The Journal of Finance*, 2009, *64* (1), 151–185.

**Caggese, Andrea and Ander Pérez-Orive**, "How stimulative are low real interest rates for intangible capital?," *European Economic Review*, 2022, *142*, 103987.

**Carvalho, Vasco M and Basile Grassi**, "Large firm dynamics and the business cycle," *American Economic Review*, 2019, *109* (4), 1375–1425.

**Castro-Vincenzi, Juanma and Benny Kleinman**, "Intermediate input prices and the labor share," *Princeton University, unpublished manuscript, https://www. castrovincenzi. com/research/blog-post-title-two-49acg (Accessed December 2 2023)*, 2022.

**Cavenaile, Laurent, Murat Alp Celik, and Xu Tian**, "Are markups too high? competition, strategic innovation, and industry dynamics," *Competition, Strategic Innovation, and Industry Dynamics (August 1, 2019)*, 2019.

**Chiavari, Andrea**, "The Macroeconomics of Rising Returns to Scale: Costumer Acquisition, Markups, and Dynamism," 2021.

**Clementi, Gian Luca and Berardino Palazzo**, "Entry, exit, firm dynamics, and aggregate fluctuations," *American Economic Journal: Macroeconomics*, 2016, *8* (3), 1–41.

**_ and _** , "On the calibration of competitive industry dynamics models," *Unpublished working paper*, 2016.

**_ and _** , "Investment and the Cross-Section of Equity Returns," *The Journal of Finance*, 2019, *74* (1), 281–321.

**Cloyne, James, Joseba Martinez, Haroon Mumtaz, and Paolo Surico**, "Short-term tax cuts, long-term stimulus," Technical Report, National Bureau of Economic Research 2022.

**Cooper, Russell W and John C Haltiwanger**, "On the nature of capital adjustment costs," *The Review of Economic Studies*, 2006, *73* (3), 611–633.

**Corrado, Carol A and Charles R Hulten**, "How do you measure a" technological revolution"?," *American Economic Review*, 2010, *100* (2), 99–104.

**Corrado, Carol, Charles Hulten, and Daniel Sichel**, "Intangible capital and US economic growth," *Review of income and wealth*, 2009, *55* (3), 661–685.

**_ , Jonathan Haskel, Cecilia Jona-Lasinio, and Massimiliano Iommi**, "Intangible capital and modern economies," *Journal of Economic Perspectives*, 2022, *36* (3), 3–28.

**Covarrubias, Matias, Germán Gutiérrez, and Thomas Philippon**, "From good to bad concentration? US industries over the past 30 years," *NBER Macroeconomics Annual*, 2020, *34* (1), 1–46.

**David, Joel M**, "The aggregate implications of mergers and acquisitions," *The Review of Economic Studies*, 2021, *88* (4), 1796–1830.

**_ and Venky Venkateswaran**, "The sources of capital misallocation," *American Economic Review*, 2019, *109* (7), 2531–67.

**Davis, Steven J, John Haltiwanger, Ron Jarmin, Javier Miranda, Christopher Foote, and Eva Nagypal**, "Volatility and dispersion in business growth rates: Publicly traded versus privately held firms [with comments and discussion]," *NBER macroeconomics annual*, 2006, *21*, 107–179.

**Deb, Shubhdeep, Jan Eeckhout, Aseem Patel, and Lawrence Warren**, "Market power and wage inequality," Technical Report, IFS Working Papers 2022.

**Doms, Mark and Timothy Dunne**, "Capital adjustment patterns in manufacturing plants," *Review of economic dynamics*, 1998, *1* (2), 409–429.

**Doraszelski, Ulrich and Jordi Jaumandreu**, "R&D and productivity: Estimating endogenous productivity," *Review of economic studies*, 2013, *80* (4), 1338–1383.

**Döttling, Robin and Lev Ratnovski**, "Monetary policy and intangible investment," *Journal of Monetary Economics*, 2023, *134*, 53–72.

**Eisfeldt, Andrea L and Dimitris Papanikolaou**, "Organization capital and the cross-section of expected returns," *The Journal of Finance*, 2013, *68* (4), 1365–1406.

**_ , Antonio Falato, and Mindy Z Xiaolan**, "Human capitalists," *NBER Macroeconomics Annual*, 2023, *37* (1), 1–61.

**Elsby, Michael WL, Bart Hobijn, and Ayşegül Şahin**, "The decline of the US labor share," *Brookings papers on economic activity*, 2013, *2013* (2), 1–63.

**Ewens, Michael, Ryan H Peters, and Sean Wang**, "Measuring intangible capital with market prices," *Management Science*, 2025, *71* (1), 407–427.

**Falato, Antonio, Dalida Kadyrzhanova, Jae Sim, and Roberto Steri**, "Rising intangible capital, shrinking debt capacity, and the US corporate savings glut," *The Journal of Finance*, 2022, *77* (5), 2799–2852.

**Foster, Lucia, John Haltiwanger, and Chad Syverson**, "Reallocation, firm turnover, and efficiency: selection on productivity or profitability?," *American Economic Review*, 2008, *98* (1), 394–425.

**Fullerton, Rosemary R, Cheryl S McWatters, and Chris Fawson**, "An examination of the relationships between JIT and financial performance," *Journal of Operations Management*, 2003, *21* (4), 383–404.

**Galy, Edith and Mary Jane Sauceda**, "Post-implementation practices of ERP systems and their relationship to financial performance," *Information & management*, 2014, *51* (3), 310–319.

**Gollin, Douglas and Christopher Udry**, "Heterogeneity, measurement error, and misallocation: Evidence from African agriculture," *Journal of Political Economy*, 2021, *129* (1), 1–80.

**Griliches, Zvi**, "Issues in assessing the contribution of research and development to productivity growth," *The bell journal of economics*, 1979, pp. 92–116.

**Grilliches, Zvi**, "R&D and productivity: Econometric results and measurement issues," *Handbook of Economics of Innovation and Technological Change, Oxford*, 1995, pp. 52–89.

**Grossman, Gene M and Ezra Oberfield**, "The elusive explanation for the declining labor share," *Annual Review of Economics*, 2022, *14* (1), 93–124.

**Grullon, Gustavo, Yelena Larkin, and Roni Michaely**, "Are US industries becoming more concentrated?," *Review of Finance*, 2019, *23* (4), 697–743.

**Gutiérrez, Germán and Thomas Philippon**, "Investmentless growth: An empirical investigation," *Brookings Papers on Economic Activity*, 2017, *48*, 89–190.

**Haskel, Jonathan and Stian Westlake**, *Capitalism without capital: the rise of the intangible economy*, Princeton University Press, 2018.

**Hopenhayn, Hugo A**, "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica: Journal of the Econometric Society*, 1992, pp. 1127–1150.

_ , "Firms, misallocation, and aggregate productivity: A review," *Annu. Rev. Econ.*, 2014, *6* (1), 735–770.

**Hopenhayn, Hugo and Richard Rogerson**, "Job turnover and policy evaluation: A general equilibrium analysis," *Journal of political Economy*, 1993, *101* (5), 915–938.

**_ , Julian Neira, and Rish Singhania**, "From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share," *Econometrica*, 2022, *90* (4), 1879–1914.

**Hsieh, Chang-Tai and Esteban Rossi-Hansberg**, "The industrial revolution in services," *Journal of Political Economy Macroeconomics*, 2023, *1* (1), 3–42.

**Hubmer, Joachim**, "The Race Between Preferences and Technology," *Econometrica*, 2023, *91* (1), 227–261.

**Karabarbounis, Loukas and Brent Neiman**, "The global decline of the labor share," *The Quarterly journal of economics*, 2013, *129* (1), 61–103.

**Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin**, "Demographic Origins of the start-up Deficit," *American Economic Review*, 2024, *114* (7), 1986–2023.

**Kaymak, Barış and Immo Schott**, "Corporate Tax Cuts and the Decline in the Manufacturing Labor Share," *Econometrica*, 2023, *91* (6), 2371–2408.

**Khan, Aubhik and Julia K Thomas**, "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics," *Econometrica*, 2008, *76* (2), 395–436.

**Koh, Dongya, Raül Santaeulàlia-Llopis, and Yu Zheng**, "Labor share decline and intellectual property products capital," *Econometrica*, 2020, *88* (6), 2609–2628.

**Lashkari, Danial, Arthur Bauer, and Jocelyn Boussard**, "Information technology and returns to scale," *American Economic Review*, 2024, *114* (6), 1769–1815.

**_ , _ , and _** , "Information technology and returns to scale," *American Economic Review*, 2024, *114* (6), 1769–1815.

**Lee, Yoonsoo and Toshihiko Mukoyama**, "Productivity and employment dynamics of US manufacturing plants," *Economics Letters*, 2015, *136*, 190–193.

**Lev, Baruch and Feng Gu**, *The end of accounting and the path forward for investors and managers*, John Wiley & Sons, 2016.

**Loecker, Jan De, Jan Eeckhout, and Gabriel Unger**, "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

**_ , _ , and Simon Mongey**, "Quantifying market power and business dynamism in the macroeconomy," Technical Report, National Bureau of Economic Research 2021.

**McGrattan, Ellen R and Edward C Prescott**, "Technology capital and the US current account," *American Economic Review*, 2010, *100* (4), 1493–1522.

**_ and _** , "Unmeasured Investment and the Puzzling US Boom in the 1990s," *American Economic Journal: Macroeconomics*, 2010, *2* (4), 88–123.

**_ and _** , "A reassessment of real business cycle theory," *American Economic Review*, 2014, *104* (5), 177–82.

**Nakamura, Masao, Sadao Sakakibara, and Roger Schroeder**, "Adoption of just-in-time manufacturing methods at US-and Japanese-owned plants: some empirical evidence," *IEEE transactions on engineering management*, 1998, *45* (3), 230–240.

**Nicolaou, Andreas I**, "Firm performance effects in relation to the implementation and use of enterprise resource planning systems," *Journal of information systems*, 2004, *18* (2), 79–105.

**Olmstead-Rumsey, Jane**, "Market concentration and the productivity slowdown," *MPRA Paper*, 2019, *93260.*

**Peters, Ryan H and Lucian A Taylor**, "Intangible capital and the investment-q relation," *Journal of Financial Economics*, 2017, *123* (2), 251–272.

**Ridder, Maarten De**, "Market power and innovation in the intangible economy," *American Economic Review*, 2024, *114* (1), 199–251.

**Santoleri, Pietro, Andrea Mina, Alberto Di Minin, and Irene Martelli**, "The causal effects of R&D grants: Evidence from a regression discontinuity," *Review of Economics and Statistics*, 2024, *106* (6), 1495–1510.

**Umble, Elisabeth J, Ronald R Haft, and M Michael Umble**, "Enterprise resource planning:

Implementation procedures and critical success factors," *European journal of operational research*, 2003, *146* (2), 241–257.

**Weiss, Joshua**, "Intangible Investment and Market Concentration," Technical Report, Working Paper 2019.

**Winberry, Thomas**, "Lumpy investment, business cycles, and stimulus policy," *American Economic Review*, 2021, *111* (1), 364–96.

**Zhang, Lichen**, "Intangible-Investment-Specific Technical Change, Concentration and Labor Share," 2019.