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) reductions in allocative efficiency. 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

Over recent decades, the US economy witnessed notable secular trends, such as increased concentration, declining labor share, and a tangible capital investment slowdown. Existing theories attribute these trends to factors like heightened market power, tax changes, and demographics.[1] Concurrently, investments in intangible capital, encompassing software and computerized information, have increased (Koh et al., 2020). Intangible capital is often immaterial, specific to the firms and plagued by investment frictions (Haskel and Westlake, 2018). This paper offers a complementary explanation, connecting these trends to shifts in firms' cost structures, triggered by firms' efficient response to shifts in production technology biased toward 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 elevated fixed and convex adjustment costs for intangible capital. A rise in intangible capital favors larger firms in the selection process, contributing significantly 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, as in Koh et al. (2020).

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 expenditures and balance sheets identifiable intangible assets. At the aggregate level our measure aligns well compared to Koh et al. (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

[1]E.g., Hopenhayn et al. (2018); De Ridder (2019); De Loecker et al. (2021); Kaymak and Schott (2023).
[2]Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017), and Ewens et al. (2019).
[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 et al. (2009), Lev and Gu (2016), Ewens et al. (2019)

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. This growth occurs at the expense of the labor input. 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).

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, time periods, firm characteristics, 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 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 ability of firms to adjust inputs to the desired levels. Thus, preventing the equalization of marginal product to marginal cost, 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

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

[5]These findings complement Peters and Taylor (2017), Belo et al. (2022), and Cloyne et al. (2022), who focus only on convex adjustment costs.

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 et al. (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.

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 highlights a divergence between micro and macro intangible capital shares. At the micro-level, there's a 7 percentage point (p.p.) increase, from

[6] These results align with case studies on enterprise resource planning (ERP) systems, highlighting substantial implementation costs and extended setup times (Umble et al., 2003; Nicolaou, 2004; Galy and Sauceda, 2014), as well as empirical research showing adjustment costs like behavior of intangible capital (Santoleri et al., 2020; Bloesch and Weber, 2022).

3% to 10%, while at the macro-level, there's a 3 p.p. rise. This divergence is due to adjustment costs acting as a constraint, limiting substantial investments in intangible capital by firms.

Moreover, IBTC explains half of the decline in 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 7 p.p. decline in the aggregate labor share. In line with Koh et al. (2020), we show that treating intangible capital investment as an expense, rather than capitalizing it, would substantially lower the decline in the 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 et al. (2020) and Barkai (2016).

Finally, the quantitative model shows that IBTC can explain between 32% and 80% of the overall rise in the dispersion in $TFPR$, as documented by Bils et al. (2020). 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 $TFPR$. Therefore, dispersion in $TFPR$ rises, implying lower allocative efficiency. However, in our framework, dispersion in $TFPR$ cannot be interpreted as misallocation, as it is in Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), because the allocation still coincides with the planner's one.

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 et al. (2023), and Ewens et al. (2019).[7] Building on these measures, we estimate the firm-level production function documenting the increase in the share of this 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 et al. (2014),

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

highlighting the role of fixed adjustment costs.[8] Peters and Taylor (2017), Belo et al. (2022) and Cloyne et al. (2022) structurally estimate convex adjustment costs finding them to be large for intangible relative to tangible capital. 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 complements studies like Lashkari et al. (2019), Aghion et al. (2019), Hsieh and Rossi-Hansberg (2019), Hopenhayn et al. (2018), De Loecker et al. (2021), Kaymak and Schott (2023), Hubmer (2023), Castro-Vincenzi and Kleinman (2022) and Chiavari (2021), which explore mechanisms unrelated to intangible capital driving some of the secular trends we study. In the realm of intangible capital, De Ridder (2019) and Weiss (2019) emphasize its role, combined with increasing market power, in recent trends. Falato et al. (2022) and Zhang (2019) highlight its interaction with financial frictions.[9] Our study contributes by using micro-level data to show novel properties of intangible capital and proposing that a significant portion of these trends arises from the economy's efficiently response to shifts in firm-level production technology, rather than solely from responses to market power or 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

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

[9] Other studies explore various aspects of intangible capital. Caggese and Pérez-Orive (2022) and Döttling and Ratnovski (2023) find slow responsiveness to monetary policy. Bates et al. (2009), Brown et al. (2009), and Altomonte et al. (2021) note its low collateral value. Grilliches (1995) and Doraszelski and Jaumandreu (2013) investigate intangible capital's contribution to productivity.

these data an excellent 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 et al., 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, 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.[10]

2.2 Intangible Capital Measurement

The measurement of intangible capital is challenging as a substantial portion of it is internally generated and the US GAAP does not allow its capitalization on the balance sheet (Lev and Gu, 2016; Ewens et al., 2019). Only externally acquired intangible capital is booked there. Online Appendix I.I.III discusses the accounting standards and related challenges to firm-level intangible capital measurement.

[10] 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.

In light of these considerations and similarly to Peters and Taylor (2017) and Ewens et al. (2019), our main measure is formed by internally generated intangible capital and externally acquired intangible capital.[11] Internally generated intangible capital is obtained through the capitalization of R&D expenditure (XRD) via perpetual inventory method, as in national accounting practice (Corrado et al., 2022):

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

where XRD is gross investment in knowledge capital deflated by the IPP price deflator, the sector-level depreciation rate δ_s is taken from Ewens et al. (2019), and the initial stock is assumed to be zero.[12]

The second component of intangible capital is the externally acquired intangible capital, given by

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

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.

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

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

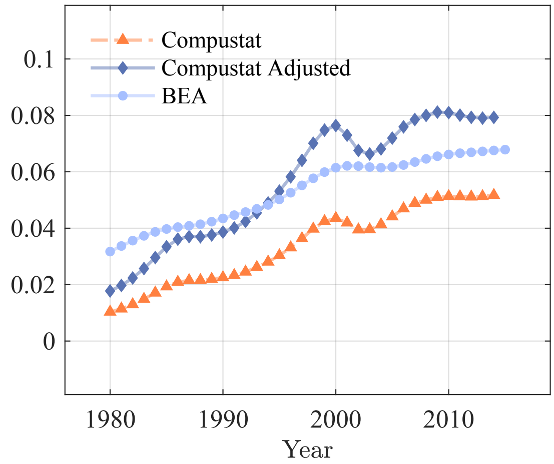
Figure 1 compares our intangible capital investment share with BEA's from Koh et al. (2020). Both show a similar increase over time. In the Online Appendix I.I.IV, we provide additional comparisons between our firm-level measure and national accounting measures and highlight that both at the firm and aggregate levels, the primary driver of intangible capital rise is the externally acquired component.[13] Despite these successes, we acknowledge

[11]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.

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

[13]Firm-level patents are highly correlated with our measure. Results are available upon request.

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 et al. (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 $\lambda = 6.25$.

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, ℓ_{ft} is the log of labor, ω_{ft} is the log of productivity, and ε_{ft} is the error term.[14] The introduction of intangible capital as an input in production is motivated by the growing evi-

[14]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.

dence that software, and intangible capital more generally, are extensively used in production (Bhandari and McGrattan, 2021; Acemoglu 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 (ω_{ft}). To address this endogeneity, we use two approaches from the empirical industrial organization literature: the cost shares (CS) approach (Foster et al., 2008) and the Ackerberg-Caves-Frazer (ACF) approach (Ackerberg et al., 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.[15] 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.

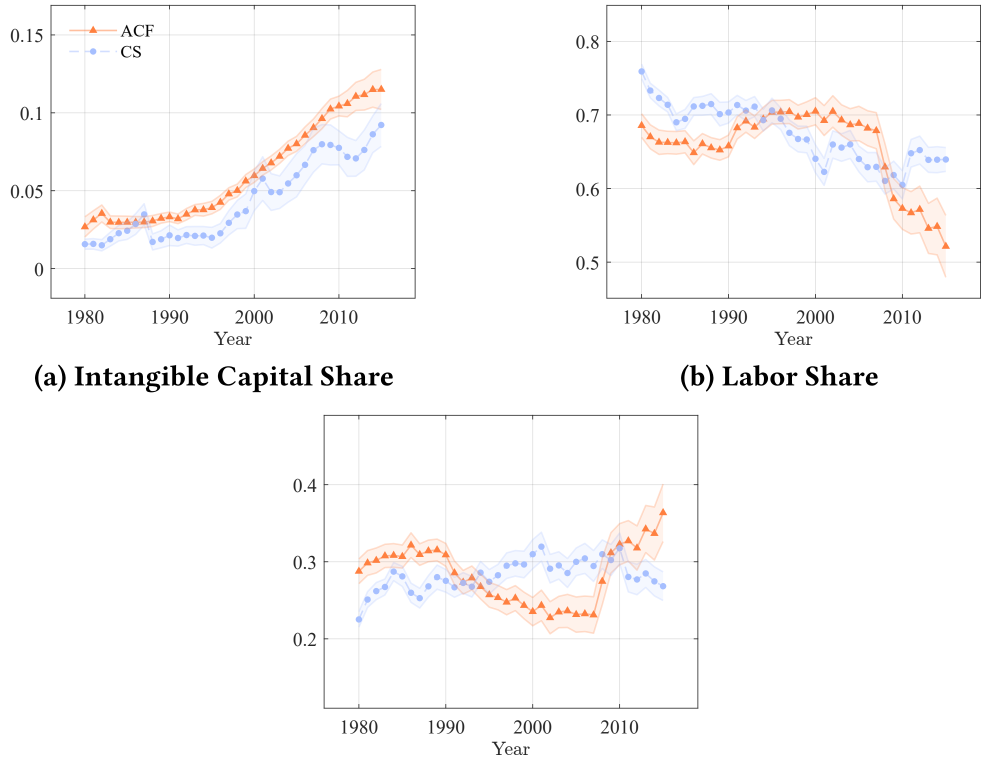
Specifically, the intangible capital share, using the CS approach, increases from 0.02 in 1980 to 0.09 in 2015, while with the ACF approach, it rises from 0.03 to 0.11. The share of labor in production, following the CS approach, declines from 0.759 to 0.639, while with the ACF approach, it drops from 0.686 to 0.521. These estimates suggest a substitution between intangible capital and labor over time. Together, 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 et al. (2013), Karabarbounis and Neiman (2013), Koh et al. (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 explain later in Section 7.

Next, we show that IBTC is robust across various permutations of production technology. It appears unaffected by assumptions on returns to scale, sectoral heterogeneity, specific functional forms of the production function, choice of variable inputs, inclusion of R&D in intangible capital, unavailability of firm-level prices, and potential measurement errors. Consistency across different variable inputs and exclusion of R&D from intangible capital suggests

[15] 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.

that the overlap between some parts of intangible capital and the wage bill is not driving our findings. Thus, we interpret the rise in intangible capital as an exogenous technological shift biased toward intangible capital at the expense of labor in production.

3.1.2 Discussion of the Assumptions

We explore two alternative models isomorphic to equation (5).

(i) Griliches (1979)' knowledge capital model. This model interprets intangible capital as an endogenous productivity shifter. The resulting production function aligns with equation (5), where $\nu k_{I,ft} + \omega_{ft}$ represents total productivity, with the first component being endogenous and the second exogenous. While maintaining the benchmark structure, parameter ν signifies intangible capital's importance for firm productivity.

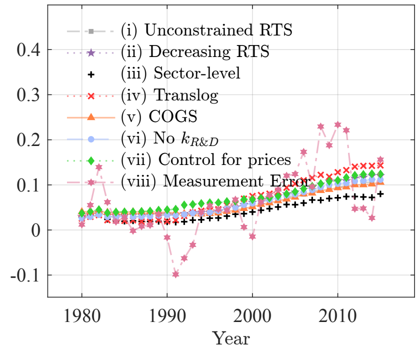
(ii) Intangible capital as a demand shifter. An alternative interpretation posits that firms use intangible capital to influence demand rather than to produce. Under common assumptions like CES demand, this interpretation is isomorphic to equation (5) as shown in Online

Appendix II.II.I.

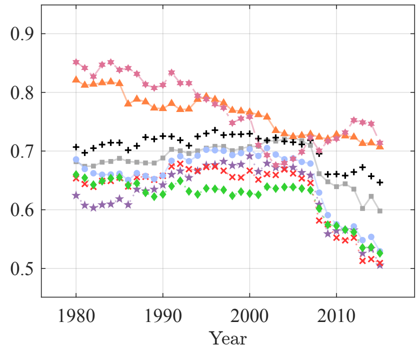
3.1.3 Robustness

Here we test the robustness of our results to the following alternative specifications: (i) unconstrained returns to scale; (ii) imposing decreasing returns to scale; (iii) two-digit sector level (NAICS 2) technology; (iv) translog production function; (v) using cost of goods sold as a variable input; (vi) excluding internally generated intangible capital ($k_{R\&D}$); and (vii) considering output and input price variation the ACF estimation. Figure 3 illustrates results from these alternatives, while Online Appendix I.III explains the details.

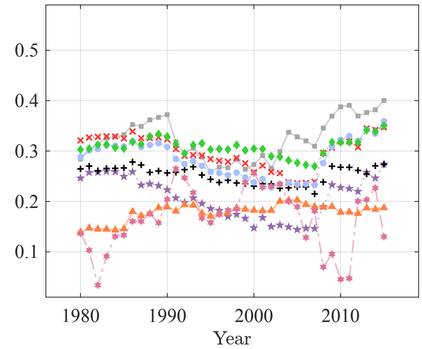
Figure 3: Trends in Input Shares: Robustness



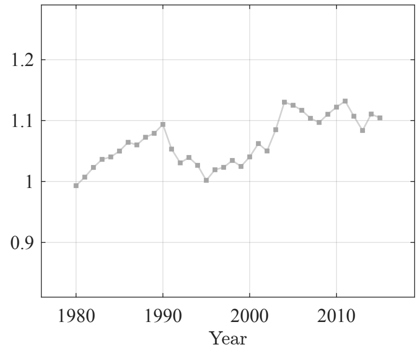
(a) Intangible Capital Share



(b) Labor Share



(c) Tangible Capital Input Share



(d) Returns to Scale

Note. The figures present the output elasticities estimated with the ACF approach and unconstrained returns to scale (dashed-dotted light gray lines with squares), with the ACF approach and decreasing returns to scale equal to 0.9 (dashed-dotted purple lines with stars), with the sector-level ACF approach (black plus signs), with the translog ACF approach (dotted red lines with crosses), with the ACF approach with COGS as a variable input (solid orange lines with triangles), with the ACF approach using only externally purchased intangible capital (solid light blue lines with circles), with the ACF approach with controls for unobservable input and output price variation (dotted light green lines with diamonds), and with the ACF approach controlling for measurement error (dashed-dotted light pink lines with hexagrams). The elasticities are estimated using a 10-year rolling windows over time.

(i-ii) Alternative returns to scale. Specifications (i) and (ii) explore the effect of returns to scale on our findings. In (i), unconstrained returns reveal an increasing trend, aligning with previous studies. Despite varying returns, our main findings of rising intangible capital

and declining labor shares persist. In (ii), assuming decreasing returns to scale equal to 0.9, common in firm dynamics literature, does not alter our empirical findings. This suggests that the specific level of returns to scale does not alter the main results.

(iii) Sector-level technology. Specification (iii) allows firms in different sectors to operate a different production technology. We retrieve sales-weighted input elasticities that are similar to our benchmark suggesting that the assumption of a homogeneous production technology across sectors is not driving our findings.

(iv) Translog production technology. Specification (iv) relaxes the log-linear relation between output and inputs using a translog production function (a second-order approximation of a CES production technology). Results remain similar to the benchmark ones.

(v) Alternative variable input. Specification (v) uses a different variable input: cost of goods sold. This input, unlike employment, does not keep track of scientists or designers employed by firms to produce intangible capital, but instead tracks only the variable expenditures used in production. This specification shows patterns similar to our benchmark.

(vi) Excluding internally generated intangible capital ($k_{R\&D}$). Specification (vi) uses only externally acquired intangible capital (k_{BS}) as intangible capital measure. This robustness shows patterns similar to our benchmark, suggesting that any overlap between capitalized R&D and labor is unlikely to drive our main findings.

(vii) Controlling for output/input price variation. Specification (vii) controls for variation in output and input prices by introducing an additional proxy variable, firm-level sales shares, in the ACF estimation procedure (De Loecker et al., 2020). We find that its inclusion does not influence our results.

(viii) Controlling for measurement error. Specification (viii) addresses measurement error in intangible capital by employing a methodology proposed by Collard-Wexler and De Loecker (2021). The presence of measurement error typically biases downward estimated input shares. Thus, without it, we would expect an even higher estimate of the input share. The methodology relies on using intangible capital investment as an instrument, which is challenging due to limited availability, as noted in Levinsohn and Petrin (2003). Despite the trade-off between addressing measurement error and maintaining statistical power, we proceed and find a larger, though less precisely estimated, increase in the intangible capital share over the sample period.[16]

[16]Due to limited intangible capital investment data, we employ the inverse hyperbolic sine transformation and

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

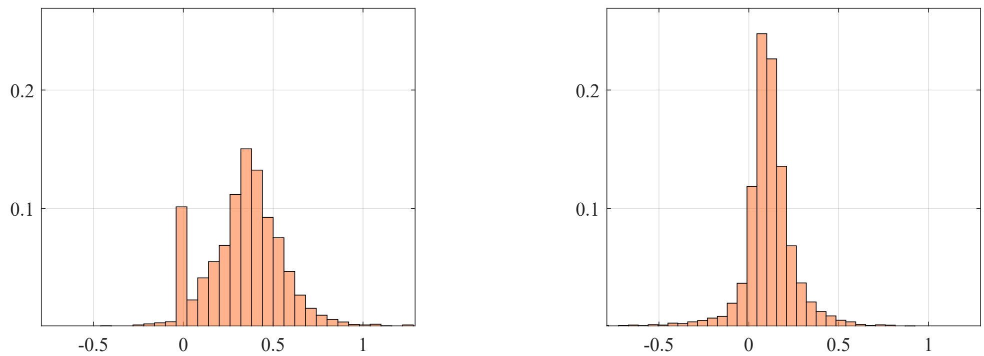
3.2.1 Investment Rate Distributions

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 δ_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 4: 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 4a shows the investment rate distribution for intangible capital. Figure 4b shows the investment rate distribution for tangible capital. The histograms are constructed by dropping from the balanced panel all the firms that never invest in intangible capital and all the observations with investment rates above 3 or below -1. Results are robust to other winsorization schemes.

use cost of goods sold instead of employee numbers as the variable input in our production function estimator. This approach aims to maximize available observations. However, for a few data points, the estimator yields a negative intangible capital input share, attributed to data loss from measurement error correction. This is a limitation linked to convergence issues in the GMM method when dealing with a small number of observations, as noted in Gao and Kehrig, 2017.

[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.

Figure 4a and 4b 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 et al., 2014; Clementi and Palazzo, 2016a). Focusing on *spike rates* and *serial correlation*, 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 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 et al., 2020; 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).

Next, we demonstrate the robustness of two key features in the investment rate distribution of intangible capital: higher positive spike rates and serial correlation compared to tangi-

[20] Aligning with the tangible capital literature, we adopt a 20% threshold for the spike rate, ensuring comparability. Importantly, our results hold across various higher thresholds, with intangible capital consistently exhibiting a high spike rate.

[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 et al., 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.

ble capital. These characteristics appear intrinsic to intangible capital investment and do *not* seem to depend on industry, time period, firm characteristics (age, size, leverage, liquidity), types of intangible capital, specifications for calculating investment rates, or the presence of measurement error.[23] In the quantitative section, we leverage these two moments to identify underlying investment frictions associated with intangible capital investment.

3.2.2 Robustness

Here, we demonstrate the robustness of our findings. We explore alternative investment rate distributions (i) across sectors, (ii) over time, (iii) among different types of firms, (iv) for various types of intangible capital, and (v) with an alternative specification. Online Appendix I.IV shows the details of these different specifications.

(i) Investment rates across sectors. Online Appendix I.IV.I outlines investment rate distribution moments across various US sectors. Intangible capital consistently shows a high positive spike rate and serial correlation in all sectors, aligning with our benchmark findings. Sectoral differences do not seem crucial in understanding the behavior of intangible capital's investment rate distribution.

(ii) Investment rates across time. Online Appendix I.IV.II details investment rate distribution moments over time. The positive spike rate and serial correlation of intangible capital investment remain relatively stable across different decades, suggesting that the properties of the investment rate distribution have remained consistent over time.

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

(iii) Investment rates across firms of different age, size, leverage, and liquidity groups. Online Appendix I.IV.III presents investment rate distribution moments for intangible capital across various firm types. This includes comparisons between young and old firms, small and large firms, high and low leverage firms, and low and high liquidity firms.[24] Intangible capital consistently shows a stable positive spike rate and serial correlation across these diverse groups. This independence from financial proxies implies that financial frictions do not seem the main driver of our findings.

(iv) Investment rates across different types of intangible capital. Online Appendix I.IV.IV details the investment rate distribution moments for externally purchased and internally produced intangible capital. Internally produced intangible capital lacks negative investments due to its construction stemming from the capitalization of a non-negative expenditure. High inaction rates come from internally generated intangible capital only, hence the conservative choice to focus only on positive spike rates and serial correlation. In fact, both types of intangible capital consistently exhibit substantially higher positive spike rates and serial correlation than tangible capital.

(v) Investment rates calculated with alternative specification. Online Appendix I.IV.V presents the moments of intangible and tangible capital investment rate distribution computed as

$$\frac{x_{j,ft}}{k_{j,ft-1}} \equiv \frac{k_{j,ft} - k_{j,ft-1}}{k_{j,ft-1}} + \delta_j, \quad j \in \{T, I\}. \tag{7}$$

We find moments that are very similar to those produced by our benchmark specification.

(vi) Investment rates in the presence of measurement error. Online Appendix I.IV.VI explores the sensitivity of our results to the presence of classical measurement error in intangible capital stock as in Collard-Wexler and De Loecker (2021). Even with substantial measurement error, intangible capital investment maintains significantly higher spike rates and serial correlation compared to tangible capital investment. This implies that the observed differences in investment behavior between the two types are unlikely to be solely attributed to measurement errors.

[24] All comparisons involve firms categorized as above or below the median for the specified characteristics.

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 et al. (2014). Without investment frictions, the marginal revenue product of capital remains unchanged in response to productivity shocks, equating the user cost of capital. Conversely, with investment frictions, such as adjustment 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

$$\log MRPK_{j,ft} \propto \log y_{ft} - \log k_{j,ft}, \quad j \in \{T, I\}, \tag{8}$$

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.[25] Our regression framework is given by

$$\log MRPK_{j,ft} = \gamma_1 \varepsilon_{ft} + \mathbf{\Gamma X_{ft-1}} + \gamma_f + \gamma_t + \nu_{ft}, \quad j \in \{T, I\}, \tag{9}$$

where ε is the innovation to log $TFPR$, i.e., total factor productivity revenue.[26] $\mathbf{X}$ is a vector of controls (capital j, $TFPR$, age, size, leverage and liquidity), γ_f is a firm fixed effect, and γ_t is a time fixed effect.[27] The coefficient of interest is γ_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

[25]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.

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

[27]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.

products (Gollin and Udry, 2021; Bils et al., 2020), we highlight that our regression accommodates both iid and fixed measurement errors in firm-level marginal revenue products. Additioanlly, to address autocorrelated measurement errors in both capital's marginal revenue, we assume observed $MRPK_{ft} = e^{\omega_{ft}} MRPK^*_{ft}$, with serially correlated ω, given by

$$\omega_{ft} = \rho\omega_{ft-1} + \eta_{ft}, \tag{10}$$

where η is the iid shocks. Substituting (10) in (9) and ρ-differentiating it we obtain the following alternative specification:

$$\begin{aligned}\log MRPK_{j,ft} &= \rho \log MRPK_{j,ft-1} + \gamma_1(\varepsilon_{ft} - \rho\varepsilon_{ft-1}) \\ &\quad + \mathbf{\Gamma X_{ft-1}} - \rho\mathbf{\Gamma X_{ft-2}} + \gamma_f + \gamma_t + \eta_{ft} + \nu_{ft}, \quad j \in \{T, I\}.\end{aligned} \tag{11}$$

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

	Baseline		Measurement Error Adjusted	
	(1)	(2)	(3)	(4)
Dependent Variable	$MRPK_{T,ft}$	$MRPK_{I,ft}$	$MRPK_{T,ft}$	$MRPK_{I,ft}$
ε_{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

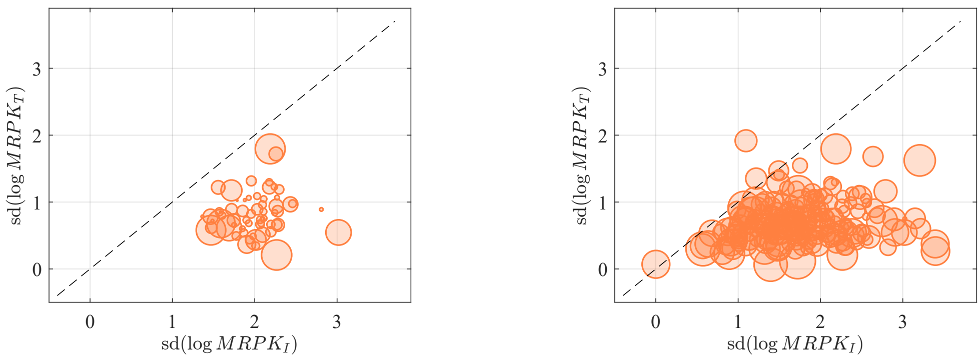
Notes. We report the coefficients from the regressions of marginal revenue product of tangible capital, $MRPK_{T,ft}$, and marginal revenue product of intangible capital, $MRPK_{I,ft}$, on revenue productivity shocks, ε_{ft}. The controls include capital, revenue productivity, sales, leverage, and liquidity. The baseline specification, which controls for classical (fixed and iid) measurement error, is shown in equation (9). The alternative specification, which controls for serially correlated measurement error, is presented in equation (11). 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 (9), while columns 3-4 display coefficients from the alternative specification (11). Notably, both tangible and intangible capital's marginal revenue product responds positively to revenue productivity shocks (γ_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.

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 5: 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 5a 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 5b 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 5 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.[28] This finding supports the presence of higher investment friction like adjustment costs associated with intangible capital investment compared to tangible capital investment.

3.3.3 Robustness

In this section, we examine the robustness of our results on the higher relative responsiveness and dispersion of the marginal revenue product of intangible capital compared to tangible

[28]Since measurement error in marginal products is mostly over time (Bils et al., 2020), taking time averages mitigates concerns about results being solely driven by measurement error.

capital. We investigate how the presence of heterogeneous markups across firms might impact our findings. Heterogenous markups distort the marginal revenue product of both types of capital because firms with different levels of market power have different incentives to suppress output and hence input demand (Peters, 2013; Edmond et al., 2018). We adjust the marginal revenue product measures for firm-level markups. Details and results are reported in Online Appendix I.V. Accounting for markups does not alter our conclusions, confirming the robustness of the higher responsiveness of intangible capital's marginal revenue product to productivity shocks. Similarly, even adjusting for markup, 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 time t, a positive mass of price-taking firms produce a homogeneous good by means of the production function $y = e^z \left(k_T^\alpha k_I^\nu \ell^{(1-\alpha-\nu)}\right)^\omega$, with α, ω, ν in $(0, 1)$, where k_T denotes tangible capital, k_I is intangible capital, ℓ is labor, and z is idiosyncratic random productivity. Idiosyncratic productivity z is driven by the stochastic process

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

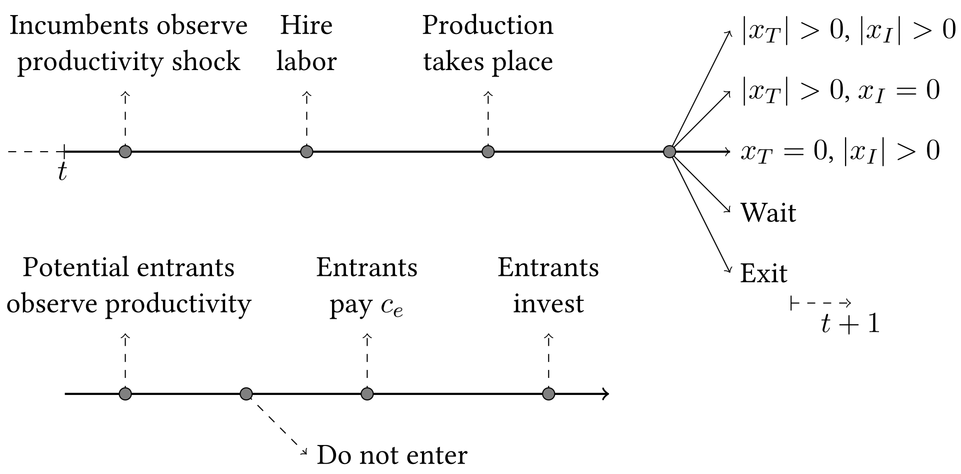
where $\varepsilon \sim \mathcal{N}(0, 1)$. The conditional distribution of z is denoted by $\Gamma(z'|z)$.

Firms discount future profits by means of 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, need for

Figure 6: Timing in the Model



plant restructuring, and worker retraining. While not admitting irreversibility, our formulation of nonconvex costs can capture a mild form of 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.

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 undepreciated 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 η. 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.[29]

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 6.

Incumbents problem. Given idiosyncratic productivity z, tangible capital k_T, and intangi-

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

ble capital k_I, the profits of an incumbent are

$$\pi(z, k_T, k_I; W) = \max_{\ell} \; e^z \left(k_T^\alpha k_I^\nu \ell^{(1-\alpha-\nu)}\right)^\omega - W\ell. \tag{12}$$

Upon exit, a firm obtains a undepreciated portion of its tangible capital k_T and intangible 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:

$$\begin{aligned}\mathcal{V}(z, k_T, k_I; W) = \pi(z, k_T, k_I; W) + \max\{&\mathcal{V}_x(k_T, k_I), \tilde{\mathcal{V}}_1(z, k_T, k_I; W) - c_f, \\ &\tilde{\mathcal{V}}_2(z, k_T, k_I; W) - c_f, \tilde{\mathcal{V}}_3(z, k_T, k_I; W) - c_f, \tilde{\mathcal{V}}_4(z, k_T, k_I; W) - c_f\},\end{aligned} \tag{13}$$

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

$$\begin{aligned}&\tilde{\mathcal{V}}_1(z, k_T, k_I; W) = \max_{k'_T, k'_I} -x_T - x_I - \mathcal{C}(x_T, x_I; k_T, k_I) + \frac{1}{R}\int \mathcal{V}(z', k'_T, k'_I; W)\Gamma(dz'|z), \\ &\qquad \text{s.t.} \quad k'_T = (1-\delta_T)k_T + x_T \quad \text{and} \quad k'_I = (1-\delta_I)k_I + x_I;\end{aligned} \tag{14}$$

the value of investing in only tangible capital is given by

$$\begin{aligned}&\tilde{\mathcal{V}}_2(z, k_T, k_I; W) = \max_{k'_T} -x_T - \mathcal{C}(x_T, 0; k_T, k_I) + \frac{1}{R}\int \mathcal{V}(z', k'_T, (1-\delta_I)k_I; W)\Gamma(dz'|z), \\ &\qquad \text{s.t.} \quad k'_p = (1-\delta_T)k_T + x_T;\end{aligned} \tag{15}$$

the value of investing in only intangible capital is given by

$$\begin{aligned}&\tilde{\mathcal{V}}_3(z, k_T, k_I; W) = \max_{k'_I} -x_I - \mathcal{C}(0, x_I; k_T, k_I) + \frac{1}{R}\int \mathcal{V}(z', (1-\delta_T)k_T, k'_I; W)\Gamma(dz'|z), \\ &\qquad \text{s.t.} \quad k'_i = (1-\delta_I)k_I + x_I;\end{aligned} \tag{16}$$

and finally, the value of waiting is given by

$$\tilde{\mathcal{V}}_4(z, k_T, k_I; W) = \frac{1}{R}\int \mathcal{V}(z', (1-\delta_T)k_T, (1-\delta_I)k_I; W)\Gamma(dz'|z). \tag{17}$$

Entrants problem. The value of a potential entrant that draws initial productivity s, where $s \sim \Lambda(s)$, is given by

$$\mathcal{V}_e(s; W) = \max_{k'_T, k'_I} -k'_T - k'_I + \frac{1}{R}\int \mathcal{V}(z', k'_T, k'_I; W)\Gamma(dz'|s). \tag{18}$$

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

4.2 Output Elasticities, Adjustment Costs, and Allocative Efficiency

Before defining allocative efficiency, we follow Hopenhayn (2014) to define $TFPR$ as

$$\begin{aligned} TFPR_{ft} &= \frac{y_{ft}}{k_{T,ft}^{\alpha} k_{I,ft}^{\nu} \ell_{ft}^{(1-\alpha-\nu)}} \\ &\propto \left(\frac{MRPK_{T,ft}}{\alpha}\right)^{\alpha} \left(\frac{MRPK_{I,ft}}{\nu}\right)^{\nu} \left(\frac{MRPL_{ft}}{1-\nu-\alpha}\right)^{(1-\alpha-\nu)}, \end{aligned} \tag{19}$$

where $MRPK_{T,ft} = \alpha\, y_{ft}/k_{T,ft}$, $MRPK_{I,ft} = \nu\, y_{ft}/k_{I,ft}$, and $MRPL_{ft} = (1-\alpha-\nu)\, y_{ft}/\ell_{ft}$. Allocative efficiency, as in Hsieh and Klenow (2009), is then defined as

$$\begin{aligned} Var(\log TFPR_{ft}) = \alpha^2 Var\left(\log MRPK_{T,ft}\right) + \nu^2 Var\left(\log MRPK_{I,ft}\right) \\ + 2\alpha\nu Cov(\log MRPK_{T,ft}, \log MRPK_{I,ft}), \end{aligned} \tag{20}$$

where $Var(\cdot)$ is the variance and $Cov(\cdot)$ is the covariance. The allocative efficiency of 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 maximum allocative efficiency. 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 (20) clarifies the relationship between intangible capital and allocative efficiency: an increase in its input share ν rises the importance of $Var\left(\log MRPK_{I,ft}\right)$, increasing overall $TFPR$ dispersion and reducing allocative efficiency.

This outcome arises from the shift away from undistorted inputs like labor to potentially distorted inputs like intangible capital.

4.3 Discussion About Modeling Choices

Here, we discuss our modeling choices concerning intangible capital and their consistency with alternative interpretations. Our model can be seen as isomorphic to one where intangible capital is a productivity or a demand shifter; see Online Appendix II.II.I for a details. In the productivity interpretation, intangible capital affects overall productivity, akin to Griliches (1979). The model remains isomorphic, but intangible capital investment represents an investment in productivity with associated adjustment costs. Alternatively, intangible capital can be viewed as a demand shifter, influencing demand without directly entering in production. Under widely used assumptions like CES demand, this interpretation is 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, δ_T, is 0.07. For intangible capital, we set the depreciation rate, δ_I, at 0.29, the average observed in our data. Production function parameters are derived from our estimates. The returns to scale, ω, are set at 0.90 (Hopenhayn and Rogerson, 1993; Khan and Thomas, 2008).[30] Idiosyncratic process persistence, ρ_z, is 0.89, and the standard

[30] 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 σ, the revenue function's curvature is ω/μ, where $\mu = \sigma/(\sigma-1)$; see Online Appendix II.II.II for details. Using $\omega = 1.1$ as in Figure 3d and a markup of 1.22 (close to the cost-weighted markup in De Loecker et al., 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.

deviation, σ_z, is 0.20 (Foster et al., 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, γ_T and γ_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).[31] The entry cost, c_e, operating cost c_f, and the parameter governing the Pareto distribution of potential entrants' productivity, η, are calibrated to match the entry rate, average size of incumbents, and average size of entrants, respectively. Finally, the measure of potential entrants, m, is set to target an equilibrium wage of 1.

Table 3: Parameters

Parameter	Value	Description
Fixed		
R	1.05	Annual interest rate
δ_T	0.07	Annual depreciation rate, tangible capital
δ_I	0.29	Annual depreciation rate, intangible capital
α	0.28	Tangible capital share
ν	0.03	Intangible capital share
ω	0.90	Returns to scale
ρ_z	0.89	Autocorrelation idiosyncratic productivity
σ_z	0.20	Standard deviation idiosyncratic productivity
Fitted		
γ_T	0.058	Convex adjustment cost k_T
γ_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
η	3.045	Scale parameter
m	0.070	Measure of potential entrants

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

[31] 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 interpret as a lower bound.

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 number of employees of a firm, and average entrant size from BDS.

more distorted compared to a frictionless benchmark.

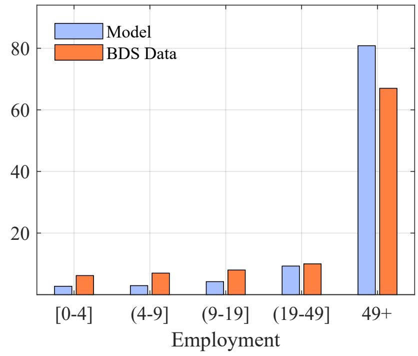
Our findings of high adjustment costs associated with intangible capital investments align with recent micro-level empirical evidence by Santoleri et al. (2020) and Bloesch and Weber (2022). The former found R&D investment responsive to subsidies, consistent with adjustment frictions, while the latter 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 et al., 1998; Fullerton et al., 2003; Umble et al., 2003; Nicolaou, 2004; Galy and Sauceda, 2014). Finally, support the notion of firm-specific with underdeveloped secondary markets hindering intangible capital trade, as suggested by Haskel and Westlake (2018).

Our parameterization is validated by the model's tangible capital to sales standard deviation equal 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.

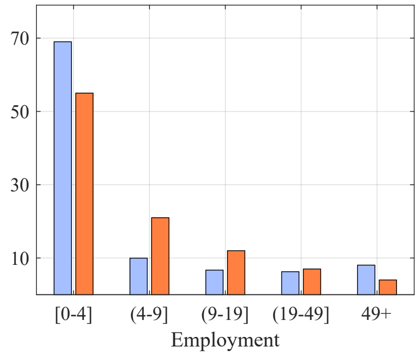
5.2 Model Cross Section and Life Cycle Validation

Figure 7 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 7a and 7b). For firm age, the model predicts similarly to the data that while only 40% of the firms are 11 year older, they account for more that 70% of total employment (Figure 7c and 7d).

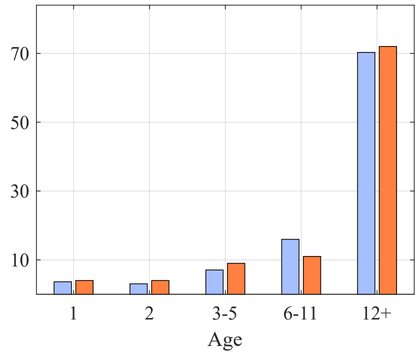
Figure 7: Size and Age Distribution: Model vs. Data



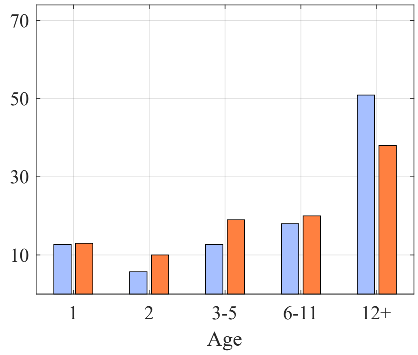
(a) Employment Distribution



(b) Firm Distributions



(c) Cohort Employment Share



(d) Age Distribution

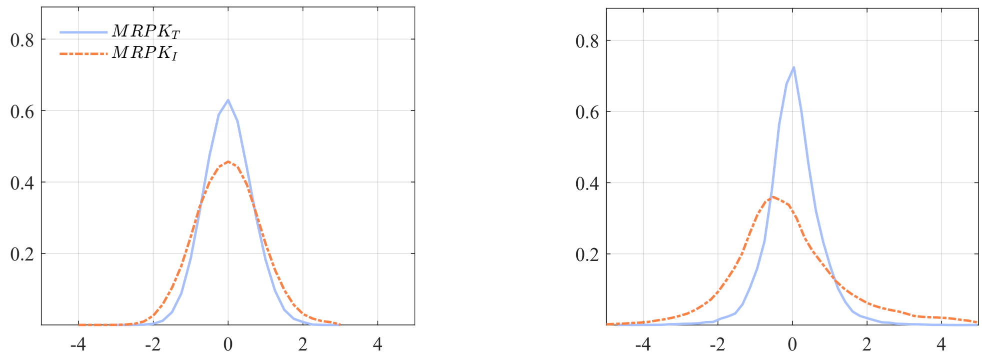
Note. The figures show the size (employment) and age distribution of the firms, in both the model and the data. Orange bars show the empirical distributions; light blue bars show the distributions from the model. The top left figure shows the employment share across different employment categories. The 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 8 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 8: Marginal Revenue Product of Tangible and Intangible Capital: Model vs. Data



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

Note. Figure 8a shows the distribution of $MRPK_T$ (solid light blue line) and $MRPK_I$ (dashed orange line) from the model. Figure 8b shows the same distributions from the data. All distributions are demeaned.

Relative responsiveness to shocks. Table 5 displays estimates of equation (9) on both model (columns 1-2) and 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.

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

	Model		Data	
	(1)	(2)	(3)	(4)
Dependent Variable	$MRPK_T$	$MRPK_I$	$MRPK_T$	$MRPK_I$
ε	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, ε. The controls include sales for columns 1 and 2 and sale, liquidity and leverage for columns 3 and 4. The baseline specification is shown in equation (9). 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.

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 inexplaining the distinct behavior of the marginal revenue product of tangible and intangible capital.

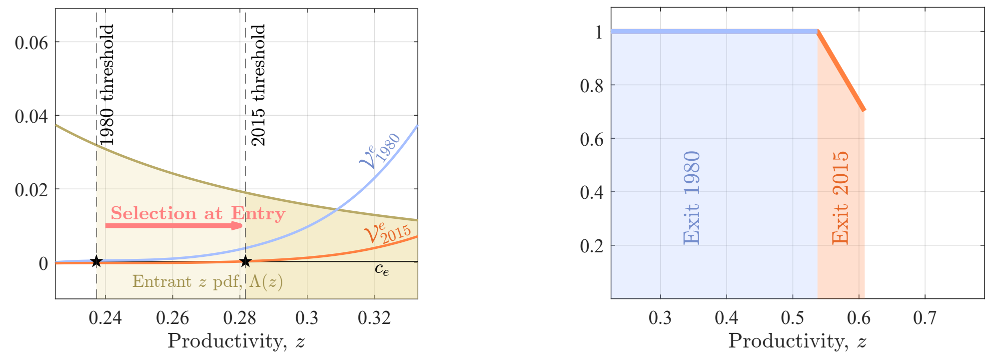
6 IBTC Mechanism and Validation

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) allocative efficiency measured by TFPR dispersion. As a frictional input like 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.

Figure 9: IBTC and Firms' Selection



(a) Entry Decision **(b) Exit Probability**

Note. Figure 9a 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 9b 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.

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 9. Figure 9a 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 9b 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 change in selection favoring more productive firms, who, anticipating future contraction due to productivity mean 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.

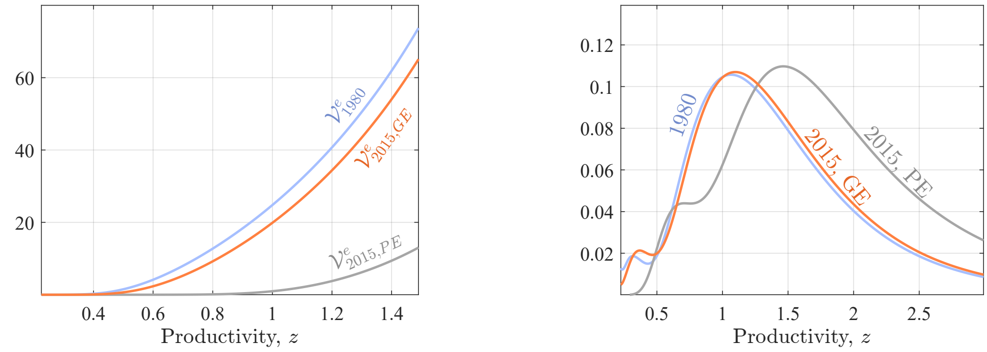
Moreover, IBTC increases average firm size, profit rate, and concentration through a change in selection and by favoring larger firms. Small firms face higher adjustment costs hindering their growth, while large firms can more easily shrink due to the high depreciation rate of intangible capital. This, 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 decline in allocative efficiency. In the model, allocative efficiency is given by equation (20). When the output elasticity of intangible capital increases, the contribution $MRPK_I$ dispersion to $TFPR$ dispersion increasese, resulting in a decline in allocative efficiency 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 10a). A similar increase in selection occurs for exiting firms, causing a rightward shift in the distribution of incumbent firms (Figure 10b).

Figure 10: General vs. Partial Equilibrium effects



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

Note. Figure 10a 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 10b 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.

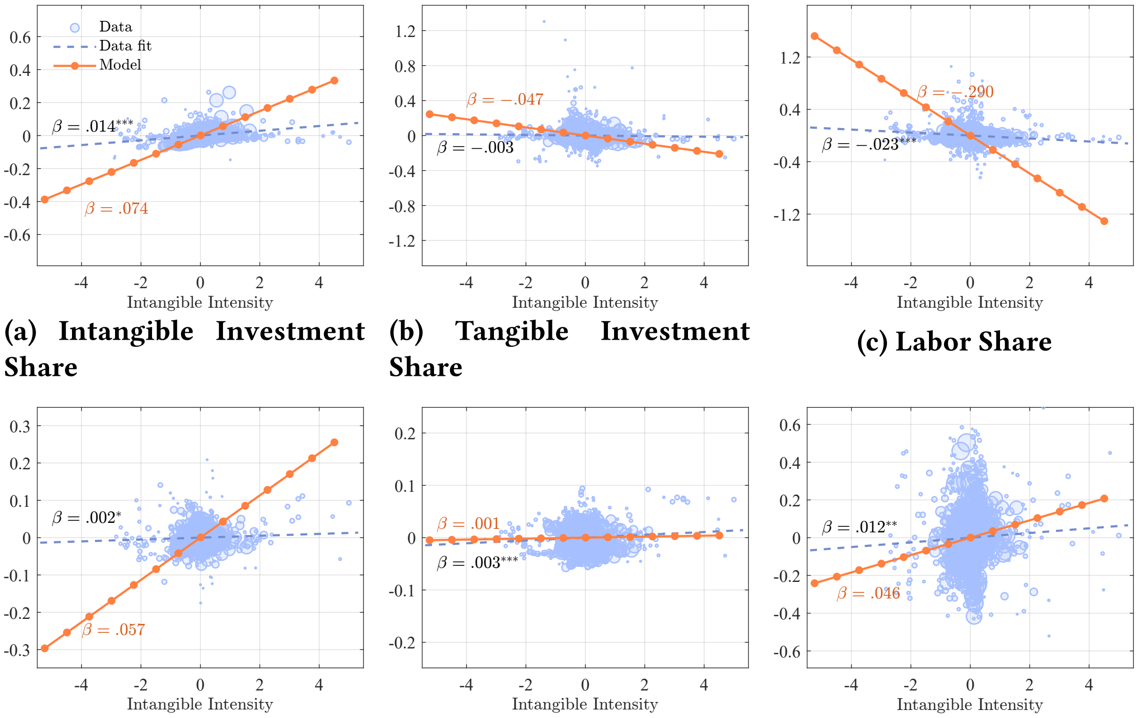
When wages adjust endogenously, the general equilibrium value of entry ($\mathcal{V}^e_{2015,GE}$) declines substantially less compared to the partial equilibrium ($\mathcal{V}^e_{2015,PE}$). This lower deline results from a wage decline caused by reduced firm entry, lowered output elasticity of labor at the firm level, and increased overall adjustment costs. This wage decline acts as 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, ν, influences sector-level factor shares, concentration, and allocative efficiency. 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 ν: 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 11 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

Figure 11: 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 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.

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, i.e., the rise in the intangible capital share in production from 0.03 to 0.10, which is the average rise across the different specifications in Section 3.1 for the period 1980-2015. Table 6 presents the results.[32]

Examining firm-level outcomes, IBTC explains the observed growth in average firm size, slightly overpredicting its extent. Similarly, it accounts for the increase in concentration, mea-

[32]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

	1980 S.S.	2015 S.S.	Change	
			Model	Data
Firm Distribution				
Avg. firm size	20.05	25.44	$+27\%$	$+15\%$
Concentration	7.9e-04	1.1e-03	$+39\%$	$+33\%$
Employment share				
firms with 250+ employees	0.447	0.480	$+3$p.p.	$+6$p.p.
Aggregate Factor Shares				
Intangible investment share	0.011	0.041	$+3$p.p.	$+4$p.p.
Tangible investment share	0.063	0.034	-3p.p.	-2p.p.
Labor share	0.680	0.613	-7p.p.	-8p.p.
Labor share pre-revision	0.688	0.639	-5p.p.	-5p.p.
Profit rate (Compustat)	0.245	0.311	$+7$p.p.	$+3$p.p.
Profit rate (BEA)	0.245	0.311	$+7$p.p.	$+5$p.p.
Aggregate Investment Rate				
Tangible investment rate	0.038	0.020	-2p.p.	-2p.p.
Allocative Efficiency				
sd($TFPR$)	0.199	0.211	$+6\%$	$+38\%$
Adjusted sd($TFPR$)	0.199	0.211	$+6\%$	$+15\%$

Note. All of the variables are calculated coherently with their definitions as used in the data. The data sources are BDS, NIPA tables, and Compustat. To calculate the empirical moments from the 1980s, we use the time window 1980-1990, whereas for the empirical moments from 2015, we simply use the values in that year.

sured 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.

Comparing the implications of IBTC with Koh et al. (2020) findings on factor shares in the non-financial corporate sector, the model captures quantitatively most of them. Remarkably, it accounts for almost the entire increase in the aggregate intangible investment share, even though the micro-level rise is 7 p.p. compared to 4 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 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 adopt the approach of Koh et al. (2020) by computing two labor shares in the model: $LS = \frac{WL}{Y}$ and LS pre-revision $= \frac{WL}{Y - X_I}$. Here, W is the wage, L is aggregate labor, Y is aggregate output net of adjustment costs and fixed costs, and X_I is aggregate intangible investment. The pre-revision labor share, excluding intangible capital from GDP calculation, declines less than the true labor share, aligning with the findings in Koh et al. (2020). This underscores that the increase in intangible capital investment is a substantial factor in the observed decline in the labor share. The model also effectively captures the decline in tangible investment share and the rise in the profit rate, through the increased selection and reallocation to larger firms explained in Section 6.

Finally, IBTC substantially accounts for the economy's declining allocative efficiency trend. 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 effectively captures the quantitative decline in allocative efficiency, especially in the adjusted case.[33]

7.2 Robustness Checks

In this section, we conduct a series of robustness tests: (i) considering only convex adjustment costs; (ii) identifying fixed adjustment costs using inaction rates instead of spike rates; (iii) recalibrating 2015 steady state adjustment costs using investment rate distribution moments; and (iv) allowing the relative price of intangible capital to decline in the 2015 steady state, as observed in the data.

In the first robustness test, we eliminate fixed adjustment costs and recalibrate the model. Results in Table 7 align closely with the benchmark, indicating that the key factor is not the presence of non-convexities in the investment process but the asymmetry in adjustment costs between the two types of investment. Check Online Appendix II.IV for detailed parameters and moments.

For the second robustness test, we recalibrate fixed adjustment costs using inaction rates instead of spike rates. Detailed parameters and moments are in Online Appendix II.IV. Results in Table 7 are akin to the benchmark and the calibration still retrieve higher fixed costs for intangible capital.

For the third robustness test, we recalibrate all the adjustment costs parameters in the post-IBTC second steady to match the 2015 investment rate distribution (Online Appendix II.IV). Results in Table 7 closely resemble the benchmark findings. Notably, recalibrating adjustment costs does not yield substantially different parameters over time, suggesting their

[33] Adjusted allocative efficiency is measured as allocative efficiency net of a 60% measurement error, as documented by Bils et al. (2020), i.e., $(1 - 0.60) \times 38\% = 15\%$.

Table 7: Quantitative Implications of IBTC: Robustness

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

Note. Column 1 (Benchmark) reports the results from the main specification. Column 2 (Convex Costs Only) shows the results of a calibration in which we allow only convex adjustment costs and no fixed adjustment costs. Column 3 (Matching Inaction Rates) shows the results of a calibration in which we identify fixed adjustment costs using inaction rates instead of spike rates. Column 4 (Alternative Adjustment Costs) shows the results when we recalibrated the model to match the investment rate moments in 2015. Column 5 (Decline Relative Price k_I) shows the results when we lower in the 2015 steady state the relative price of intangible capital, as we see in the data over the same period. Colum 6 (Data) reports the data from Compustat and BDS.

structural nature.

For the fourth robustness test, we estimate a 20% decline in the relative price of intangible capital from 1980 to 2015. This is incorporated into the model by adjusting the value functions (14)-(18) accordingly. The findings in Table 7 remain consistent with the benchmark calibration, indicating a mild role for declining relative price of intangible capital.

7.3 IBTC, Market Power, and Policy Implications

As production technology leans towards intangibility, 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 decline in allocative efficiency is attributed to technological constraints, and the decentralized equilibrium aligns with the social planner's allocation. Our findings propose that 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 factors, like the rise in market power (De Loecker et al., 2020), operating in the economy. Both IBTC and increased market power can coexist and complement each other, explaining the quantitative margins that IBTC alone cannot fully account for. For instance, in an extended model allowing for differentiated goods where markups correlate with firm size, e.g. Edmond et al. (2018), a technological change favoring larger firms would shift market shares toward high-markup firms. This aligns with the perspective that changes in cost structures, specifically higher fixed costs, contribute to the increase in market power (De Ridder, 2019; De Loecker et al., 2021), offering a potential microfoundation for elevated fixed costs through the rise of intangible capital with associated high adjustment costs.

In such an environment where IBTC contributes to rising markups, we would likely observe a larger decline in both the labor share and allocative efficiency. Following Edmond et al. (2018), increased market power in such an extended model has two primary effects: it lowers aggregate employment due to firm-level output supression, reducing the labor share, and it induces misallocation of resources, arising from heterogeneous markups. This dispersion in markups introduces a wedge in the first-order conditions of firms, leading to inefficiencies in resource allocation. Market power, therefore, appears a likely candidate contributing to the US secular trends, potentially accounting for parts of the decline in the labor share and allocative efficiency beyond what IBTC alone can explain.

We conclude emphasizing that, even though in this alternative framework the decentralized allocation would not coincide with the social planner one, the implementation of the social planner allocation, through any potential optimal policy, would coincide with the allocation in our baseline framework. Thus, while the extended framework could suggest desirable policy interventions, our main finding suggests that a significant portion of observed macroeconomic trends in the US can be the by-product of the efficient response of the economy to changes in the firm-level production technology.

8 Conclusion

This paper contributes to understanding intangible capital and its role in reconciling major 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, and diminished allocative efficiency. 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.

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