Intangible Capital and (Mis)measured Productivity*

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ABSTRACT

We study how omitting intangible capital from production functions distorts firm-level productivity measurement. Using a novel dataset of nearly 21,000 U.S. mergers and acquisitions from 2002 to 2024—covering about $15.5 trillion in acquired assets—we observe market-based valuations of targets' tangible and intangible assets immediately prior to acquisition. For each target, we estimate productivity using identical production-function specifications with and without intangible inputs. Incorporating these inputs substantially reshapes measured total factor productivity (TFP): more than 70% of firms change TFP rank, with some shifting by up to eight deciles. The average absolute change in firm-level TFP is 69%, with sector-level changes exceeding 94% in manufacturing. Intangible-adjusted TFP better predicts future growth in sales, sales per employee, and R&D investment, indicating that it captures economically meaningful differences in operating efficiency. While largely unreflected in public equity valuations, intangible-adjusted TFP is strongly associated with acquisition deal premiums, where due diligence reveals private information about firm efficiency.

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1. Introduction

Economists have long documented large and persistent differences in firm-level productivity, even among firms operating within narrowly defined industries (Syverson, 2004; Hsieh and Klenow, 2009). These differences play an important role in shaping aggregate growth, market structure, and the allocation of resources across firms.[1] Yet despite their importance, explaining the sources of this heterogeneity remains a central challenge for economic analysis and policymaking (De Loecker and Syverson, 2021).

A key difficulty is that productivity is not directly observed. Instead, it is estimated using production frameworks that relate output to observed inputs, most commonly labor, tangible capital, and intermediate materials. In modern firms, however, a large and growing share of value is generated by intangible capital, whose economic importance now rivals that of tangible capital but is almost entirely unobserved in accounting data and thus omitted from standard production frameworks. As a result, a substantial portion of estimated productivity may reflect differences in unobserved intangible inputs rather than true efficiency—an important but still unresolved measurement challenge raised by Syverson (2011).

This motivates three key questions that this paper aims to address. First, how large is the contribution of intangible capital to firms' production once these inputs are measured and incorporated into the production function? Second, to what extent does omitting intangible inputs distort conventional measures of firm-level productivity, including productivity levels, dispersion, and growth? Third, does accounting for intangible capital improve the economic information content of measured productivity, as reflected in its ability to explain variation in firm performance and to be priced by market participants?

The absence of empirical evidence on these questions is unlikely to reflect a lack of economic relevance. Intangible assets such as customer relationships, proprietary technologies, and brand capital are widely viewed as central to firm value, competitive advantage, and long-run growth (Corrado et al., 2009; Crouzet et al., 2022a; Bronnenberg et al., 2022). These assets feature prominently in discussions of declining business

[1] Early empirical evidence documenting these patterns is reviewed in Bartelsman and Doms (2000). Syverson (2011) surveys the empirical literature examining why firms differ in their productive abilities. A related theoretical literature shows how such differences lead to the reallocation of resources toward more productive producers (e.g., Jovanovic (1982); Hopenhayn (1992); Ericson and Pakes (1995); Melitz (2003)).

dynamism, rising market power, falling labor share, and productivity growth. If differences in intangible capital are substantial, standard productivity measures may systematically misstate both the level and dispersion of firm productivity, with implications for how economists assess resource allocation, firm performance, and policy outcomes. While prior work has emphasized the macroeconomic importance of a limited set of intangible inputs, we know far less about how quantitatively important intangible inputs are for firm-level productivity measurement and whether correcting this mismeasurement changes the interpretation and pricing of productivity.[2]

Empirical progress on these issues has been limited primarily by data constraints. Accounting reports provide detailed information on firms' tangible capital (e.g., balance-sheet assets), and intermediate materials and labor expenses (e.g., COGS and SG&A), but offer little direct information on most forms of their internally generated intangible capital. This limitation arises because accounting standards require that nearly all internally generated intangible investments be expensed rather than capitalized in financial reporting. As a result, existing studies typically proxy for intangible inputs using expenditure-based measures that convert flows into stocks of intangible capital. However, expenditure-based approaches require assumptions about how investment flows map into productive capital stocks and how that capital depreciates over time—parameters that are unobserved outside the firm—making it difficult to distinguish productivity differences driven by unobserved capital accumulation from differences in true efficiency.

To answer our questions above, we exploit a unique institutional feature of mergers and acquisitions (M&As) that makes otherwise unobservable intangible capital visible. In M&A transactions, accounting standards require the acquirer to allocate the total purchase price across all acquired assets at fair value, including identifiable intangible assets.[3] We exploit this feature to assemble novel data on target firms' intangible capital. Our dataset is constructed from nearly 21,000 U.S. mergers and acquisitions involving public

[2]For example, McGrattan (2020) uses theory and recently revised U.S. national accounts to estimate U.S. total factor productivity at both the aggregate and industry levels. However, the national accounts capitalize far fewer categories of intangible capital than those we document and entirely omit customer data, which we show has become the largest category of intangible assets acquired in the U.S. economy in recent decades.

[3]In purchase price allocations, the portion of the transaction price not attributable to identifiable tangible or intangible assets is recorded as goodwill. Merger-related premiums, expected synergies, and other residual components of deal value are therefore reflected in goodwill rather than in the fair values assigned to identifiable intangible assets.

firms between 2002 and 2024, representing approximately $15.5 trillion in assets. These purchase price allocations provide market-based valuations of intangibles at the firm–asset level—information that is otherwise unavailable in standard accounting data. They allow us to observe the composition, valuation, and useful lives of a broad set of intangible assets of the standalone target firm immediately prior to acquisition. We incorporate these market-valued intangible inputs into a standard production-function framework to quantify the contribution of intangible capital to output. We then assess how much conventional productivity measures are distorted by omitted intangible inputs, and evaluate whether productivity—once adjusted—has clearer economic and valuation implications.

We begin by documenting several stylized facts about intangible capital. First, as shown in Figure 1(a), identifiable intangible assets such as customer data, developed technology, and brands have risen sharply in economic importance, increasing from roughly one-third

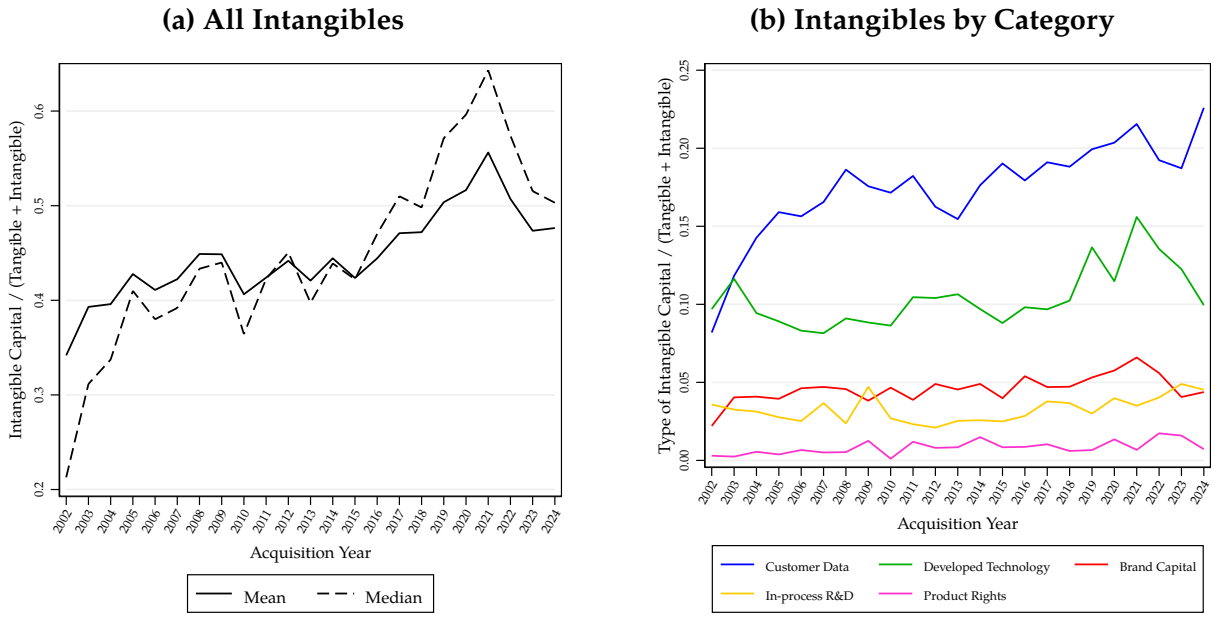


Figure 1.—Proportion of Acquired Intangibles in M&As. Figure 1(a) plots the mean and median ratios of acquired intangible capital to acquired tangible and intangible capital from 2002 to 2024. Panel (b) plots the mean ratios of the value of acquired customer data, developed technology, brand capital, in-process R&D, and product rights to the value of acquired tangible and intangible capital from 2002 to 2024. Data used to plot the figures are described in Section 3.

to more than one-half of total acquired asset value since the early 2000s. Customer data, which is currently not capitalized in the U.S. national accounts, is now the single largest category of intangible capital, roughly 23% of total acquired assets, accounting for over $1.1 trillion in total value in our sample (Figure 1(b)). Second, the assumed economic

lives of key intangible assets—especially customer data and developed technology—have lengthened substantially over time. These longer useful lives strongly predict higher asset valuations, underscoring their relevance for production. Overall, this evidence suggests that intangible capital plays a significant and increasing role in production.

To quantify this role, we next estimate production functions for U.S. publicly traded target firms as standalone entities in the year immediately prior to acquisition.[4] Although these firms account for only 1,169 (5.6%) of the targets in our sample, they span all sectors and years and represent more than half of the total value of assets acquired, approximately $8 trillion. For each target firm, we observe total revenue (output), labor, and intermediate materials from financial statements filed in the year prior to acquisition. Combining these measures with data on tangible and intangible capital valued at market prices, we estimate production functions both with and without intangible capital for the pre-acquisition year. This design allows us to quantify the contribution of intangible capital to output while isolating estimates from the effects of the merger itself.

These estimates reveal that intangible capital constitutes a large and economically meaningful input to production. When market-valued intangible assets are included, identifiable intangibles collectively account for roughly 12 percent of output—comparable in magnitude to the contribution of tangible capital (14 percent). Customer data, developed technology, brand capital, and product rights all positively relate on output, while in-process R&D relates negatively, reflecting the fact that early-stage innovation has not yet translated into current revenue.[5] Consistent with the documented rise in the economic importance of intangible capital, this contribution increases sharply over time: since 2012, the start of the second half of our sample, the combined output share of key intangible assets rises to 22 percent.

To further establish the economic relevance of these market-based measures of intangible capital, we show that firms' identifiable intangible assets are strongly reflected in their equity valuations. Incorporating intangible assets into book value substantially narrows the market-to-book gap, bringing it close to one, and variation in market-to-book ratios is

[4]For private target firms, detailed pre-acquisition financial statements are not publicly available, preventing the construction of consistent measures of output, labor, and intermediate inputs prior to acquisition.

[5]In-process R&D is negatively related to output, while developed technology is positively related, indicating that nascent innovation temporarily lowers measured productivity before yielding future gains, revealing the productivity "J-curve" described by Brynjolfsson et al. (2021).

systematically related to the composition and magnitude of intangible capital, consistent with investors capitalizing the expected future returns to these assets.

Because conventional productivity measures omit intangible inputs, measured total factor productivity (TFP) can differ substantially depending on whether these assets are included in the production function. Comparing firm-level TFP estimated with and without intangible capital, we find that nearly 70 percent of firms change their TFP decile ranking, with 25 percent shifting by three to eight deciles.[6] The mean absolute change in firm-level TFP is approximately 69 percent, and sector-level revisions are even larger—exceeding 94 percent in manufacturing. These re-rankings occur throughout the productivity distribution and materially alter both within-sector dispersion and cross-firm comparisons of efficiency.

Importantly, the direction of these TFP revisions aligns with the economic role of different intangible inputs. Intangible assets that contribute positively to current output—such as customer data, developed technology, and brand capital—are systematically associated with downward revisions to measured TFP once included as inputs, indicating that their exclusion leads to overstated productivity. By contrast, in-process R&D, which reflects early-stage innovation that does not yet generate revenue, is associated with upward revisions to TFP when accounted for explicitly. This asymmetry helps explain why productivity often appears depressed during periods of intensive innovation and highlights the importance of distinguishing between realized and in-progress intangible capital (Brynjolfsson et al., 2021).

Incorporating intangible capital reshapes measured productivity dispersion in important ways. Relative to TFP estimated from production functions that exclude intangible inputs, intangible-adjusted TFP exhibits substantially greater dispersion, particularly in manufacturing. Including intangible inputs widens the interquartile range of manufacturing TFP by roughly 60 percent, while the 90–10 and 95–5 percentile gaps expand by 34 and 78 percent, respectively. Notably, this widening is driven by heterogeneity in intangible composition: firms with greater exposure to in-process R&D shift upward in the TFP distribution, whereas firms whose intangible capital is concentrated in customer-related assets and developed technologies tend to shift downward. These asymmetric movements

[6]Throughout the paper, TFP refers to revenue-based TFP.

are concentrated in the upper tail, amplifying dispersion and raising mean manufacturing TFP by more than 44 percent relative to estimates that exclude intangible capital. Together, these results highlight the importance of accounting for both deployed and undeployed intangibles when measuring firm productivity.

We also show that accounting for intangible capital materially alters measured productivity growth, reshuffling firms' TFP growth rankings: 61 percent of firms shift by at least one decile, and 15 percent shift by three or more. Our findings further reveal that unadjusted TFP understates growth among firms at the 90th and 75th percentiles while overstating it for firms at the 25th and 10th percentiles, and that these differences persist over time.

Beyond these distributional effects, incorporating intangible inputs strengthens the economic interpretation of productivity measures. When intangible inputs are omitted from the production function, their contribution is mechanically absorbed into measured TFP, making it less informative about firms' underlying productivity-driven growth potential. Consistent with this mismeasurement, we find that intangible-adjusted TFP is positively associated with sales growth, sales per employee growth, and R&D investment, whereas unadjusted TFP is unrelated. Taken together, these results indicate that omitting intangible capital distorts not only measured productivity levels, dispersion, and growth but also reduces TFP's usefulness as a forward-looking indicator of firm performance.

Finally, we examine whether intangible-adjusted productivity is priced by investors and acquirers. In public equity markets, we find a positive but statistically insignificant relationship between intangible-adjusted TFP and market-to-book ratios, consistent with productivity being difficult to disentangle from intangible capital and other unobservables using publicly available information. In contrast, acquisition prices provide a setting in which acquirers obtain access to detailed non-public information through extensive due diligence. Using M&A deal premiums, we show that productivity is priced by acquirers, but only when it reflects true operating efficiency rather than intangible-related mismeasurement. Adjusted-TFP alone explains roughly 15 percent of the cross-sectional variation in deal premiums. Consistent with an information advantage, the positive association between deal premiums and productivity is concentrated among firms whose productivity is understated when intangible inputs are omitted from the production

function, suggesting that sophisticated buyers pay for efficiency revealed after accounting for intangible capital.

Our findings make several contributions to the literature, discussed in Section 2. Section 3 describes the data and presents descriptive statistics. Section 4 quantifies output elasticities of inputs. Section 5 examines the relationship between market values and intangible inputs. Section 6 analyzes the implications of incorporating intangible capital for productivity measurement. We conduct additional analyses in Section 7, and conclude in Section 8.

2. Related Literature and Contribution

Our paper contributes to the growing literature on intangible capital as a key input in production. A crucial first step in understanding the drivers of productivity and economic growth is to determine whether and to what extent intangible inputs contribute to output (Syverson, 2011; Karabarbounis and Neiman, 2019). A significant challenge in studying intangible assets in production is that their stocks are largely unobservable to those outside the firm. Prior research has addressed this limitation by using estimates, surveys, or focusing on narrow contexts, often examining a single type of intangible asset such as technology or knowledge capital (e.g., Brynjolfsson and Hitt, 1995; Lev, 2000; Bontempi and Mairesse, 2015; Chiavari and Goraya, 2025), organizational capital (e.g., Eisfeldt and Papanikolaou, 2013), management practices (e.g., Bloom and Van Reenen, 2007; Bender et al., 2018; Adhvaryu et al., 2023), or data (Abis and Veldkamp, 2024).[7] Another challenge is that future stocks of intangible capital may initially appear as outputs—for example, in-process R&D—making them especially difficult to estimate (Brynjolfsson et al., 2021). We advance the literature by leveraging comprehensive, transaction-level data on firms' tangible and intangible assets—including the stock of in-process R&D—to identify which types of intangible capital drive production at both the sectoral and aggregate levels. This approach allows us to estimate the output shares of all identifiable intangible assets within a unified framework. In doing so, we build on the work of Corrado et al. (2009), who examine national-level factor shares using capital stock estimates for a more limited set of intangible inputs.

[7] For methods of estimating the stock of intangible capital, see Lev and Sougiannis (1996), Hulten and Hao (2008), Falato et al. (2022), and Iqbal et al. (2025).

Our study also contributes to the extensive literature on total factor productivity (TFP) and economic growth, particularly research on the role of intangible capital (e.g., Corrado et al., 2009; McGrattan, 2020; De Loecker and Syverson, 2021; Brynjolfsson et al., 2021; Crouzet and Eberly, 2021; Crouzet et al., 2022b). We contribute by showing that incorporating firms' stocks of intangible capital into the production function leads to substantial shifts in within-firm measured TFP. To our knowledge, this is among the first empirical studies to both quantify these shifts and identify which intangible inputs drive them, and in which direction. Understanding the extent to which the output share of unmeasured intangible capital inputs is misattributed to TFP is vital to estimating true productivity (Syverson, 2011), and for understanding "how much measured productivity is affected by factors other than intangible capital" (De Loecker and Syverson, 2021, p.155). Prior research has struggled with this issue because intangible capital is difficult to observe. By contrast, our data enable us to directly measure these intangible assets, providing new insights at both the sectoral and aggregate levels.

Two of the key findings from our study—that customer data is now the economy's largest intangible asset and that it substantially influences production across major sectors—also connect our work with the expanding literatures that study the increasing economic importance of customer-related intangible capital (e.g., Barth et al., 1998; Belo et al., 2014; Gourio and Rudanko, 2014; Dou et al., 2021; Belo et al., 2022; Bronnenberg et al., 2022; He, 2022; He et al., 2024) and data (e.g., Corrado et al., 2022; Veldkamp, 2023; Abis and Veldkamp, 2024; Veldkamp and Chung, 2024; Farboodi and Veldkamp, 2024; Farboodi et al., 2025), and to the broader policy debate on whether such data should be measured and capitalized in national accounts (e.g., Rassier et al., 2019; Corrado et al., 2022; Strassner, 2024). Our study contributes to these discussions by distinguishing customer data from other forms of intangible capital, allowing us to quantify their separate contributions to output and evaluate their relative importance.

Our final contribution lies in identifying a likely factor behind the increasing importance of intangible capital in production: the extended useful life of these assets. Understanding how intangible assets depreciate is crucial for estimating intangible capital stocks, which in turn affects the measurement of factor shares, investment returns, and the relationship between intangible capital and firm value (e.g., Hall, 2001; Peters and Taylor, 2017; Crouzet

and Eberly, 2023), as well as its connection to productivity and growth (e.g., Van Ark et al., 2009; Corrado et al., 2009; Crouzet and Eberly, 2019; McGrattan, 2020; Crouzet and Eberly, 2021; Brynjolfsson et al., 2021). Despite its importance, existing research has lacked direct data on firms' private depreciation rates for intangible capital, relying instead on estimates or indirect inferences from empirical approaches (e.g., Hall, 2005; Peters and Taylor, 2017; Ewens et al., 2025). We provide direct evidence on the economic life of intangible assets using comprehensive data disaggregated by asset type, year, and sector. Doing so reveals important trends not previously documented in the literature—most notably, the sharp increase in the useful life of customer data. Linking asset longevity to transaction values, we further demonstrate that useful life is a strong predictor of value.[8]

3. Data and Stylized Facts

With the assistance of a team of Certified Public Accountants, we hand-collected and systematically categorized the values of all tangible and intangible assets, as well as debt, acquired through mergers and acquisitions (M&A) by all U.S. publicly listed firms from 2002 to 2024.[9] Conducting this data collection requires substantial accounting expertise for at least two reasons. First, mergers and acquisitions vary considerably in both complexity and the composition of assets acquired. Second, firms differ in their reporting practices and in the terminology used to describe these transactions.[10] For 99.4% of the transactions with identifiable intangible assets, our team also gathered data on firms' estimated useful life of the intangible assets. The final dataset consists of nearly 21,000 M&A deals, totaling approximately $15.5 trillion in acquired tangible and intangible assets, and represents, to the best of our knowledge, the most extensive dataset of its kind.[11] This section describes

[8]We also contribute to the body of accounting research that investigates how financial reporting influences resource allocation, productivity, and economic growth (e.g., Barrios et al., 2019; Hann et al., 2020; Breuer, 2021; Choi, 2021; Berger and Tomy, 2024; Liu and Zhang, 2024), and to the broader debate on the economic consequences of capitalizing versus expensing intangible investments (e.g., Lev and Zarowin, 1999; Lev, 2000; Kanodia et al., 2004; Kanodia and Sapra, 2016). The accounting literature has examined the connection between accounting and productivity measurement since at least Banker et al. (1989).

[9]In Supplemental Appendix A.1, we explain why it is necessary to limit our data collection to this set of firms and these years.

[10]Each M&A disclosure is first reviewed to assess whether it reports gross or net asset values. If only net asset values are reported, reflecting the subtraction of liabilities, we exclude the deal from our final sample, as these values are biased downward.

[11]A growing literature uses smaller samples of purchase price allocations in various settings (e.g., Shalev et al., 2013; Wangerin, 2019; He, 2022; He et al., 2024; Davydova, 2024; Ewens et al., 2025; Kepler et al., 2025).

these data and provides initial findings.

3.1 Intangible Capital and Useful Life Data

We obtain our data from Purchase Price Allocations (PPA) found in annual Securities and Exchange Commission (SEC) 10-K filings made by all U.S. publicly listed firms. With limited exceptions, firms are prohibited by U.S. Generally Accepted Accounting Principles (U.S. GAAP) from reporting the values of internally generated intangible capital. However, accounting standards require firms to report the values of intangible assets acquired in M&A deals through PPAs. Section 3.2 describes the PPA process and Supplemental Appendix A.1 provides an example of a PPA disclosure.

The PPA data include values assigned by the firm to identifiable intangible assets—non-physical assets separable from the company, such as customer data, developed technology, and brands—as well as goodwill. In total, we compile data on thirty categories of identifiable intangibles, which are described in Supplemental Appendix A.2.

For each category of identifiable intangible assets, we also collect the firm's disclosed estimates of useful life. Supplemental Appendix B explains how firms make these estimates. These data provide new, systematic evidence on the assumed economic life of these intangible assets across different asset types, industries, and time periods.

Other data sources, as well as our method for assigning firms to sectors, are described in Supplemental Appendix C. As shown in Supplemental Appendix C.2, the three largest sectors—manufacturing (33.1%), services (25.5%), and finance (19.1%)—represent about 80% of the nearly 21,000 M&A deals in our sample.

3.2 A Background on Purchase Price Allocations

Under U.S. GAAP, ASC 805 requires firms to allocate the purchase price of an acquisition to the acquired identifiable assets and liabilities based on their estimated fair values—a process known as the Purchase Price Allocation (PPA). This allocation shapes post-acquisition financial reporting, as it determines how assets are recognized, amortized, and depreciated, as well as how any potential future impairments are recorded. Consequently, these accounting treatments have a direct impact on reported earnings.

The PPA process involves applying a range of valuation methodologies to estimate the fair value of both acquired tangible and intangible assets. These methodologies typically

fall into three standard approaches: the income approach, which values assets based on their future expected cash flows; the market approach, which values assets on observable transactions for comparable assets; and the cost approach, which estimates values based on the replacement cost of the assets (PwC, 2022). We discuss these approaches in more detail in Supplemental Appendix D.

3.3 Initial Findings

Figure 1(a), plots the mean of the ratio of intangible assets to the sum of intangible and tangible assets for our sample of 20,963 deals. The figure shows a clear upward trend. Between 2002 and 2024, intangible assets increased from approximately one-third to about one-half of total acquired assets on average. In other words, in recent years, acquirers have allocated as much—or more—value on intangible assets as on tangible ones. The dashed line in the figure, which shows the median ratio, depicts an even sharper rise.

Table 1, Panel A, reports the total values and shares of acquired tangible assets, identifiable intangible assets, and goodwill from 2002 to 2024. The combined value of all asset types is approximately $15.5 trillion, with about 20% allocated to identifiable intangible assets. Panel B presents the ten largest categories within this group. Customer data is the most significant, exceeding $1.1 trillion—more than double the value of brand capital, the second-largest category, and nearly three times that of developed technology.

Panel A. Acquired Assets		
Assets	Amount ($M)	Percent
Tangible assets	9,065,915	58.3 %
Identifiable Intangible assets	3,013,682	19.4 %
Goodwill	3,478,914	22.4 %
Total	15,558,511	100 %
Panel B. Identifiable Intangible Assets		
Category	Amount ($M)	Percent
Customer data	1,163,112	38.6 %
Brand capital	448,058	14.9 %
Developed technology	409,561	13.6 %
Product rights	247,710	8.2 %
In-process R&D	245,732	8.2 %
FCC licenses	86,883	2.9 %
Other intangible assets	71,033	2.4 %
Franchise agreements	69,852	2.3 %
Other licenses	58,577	1.9 %
Distribution agreements	34,153	1.1 %
Total	2,834,671	94.1 %

Table 1.—Summary Statistics. This table presents summary statistics for the sample of mergers and acquisitions. Panel A presents the values and percents of assets acquired across all 20,963 deals. Panel B presents the values and percents of the ten largest categories of identifiable intangible assets.

Figure 1(b) shows trends in the average of customer data, developed technology, brands, in-process R&D, and product rights relative to the sum of intangible and tangible assets. Three patterns stand out. First, the rising importance of customer data is evident: between 2002 and 2024, its share more than doubles, rising from less than 10 percent to over 22 percent of total acquired assets.[12] Second, a sizeable gap develops between customer data and developed technology. Third, brands, in-process R&D, and product rights remain largely flat over the period.[13]

We next examine firms' assumptions about the useful lives of acquired intangibles. Our category-level data, drawn from firms' public disclosures, shed new light on how acquirers expect these assets to generate value over time. Figure 2 plots useful life estimates for customer data, developed technology, and brands.[14]

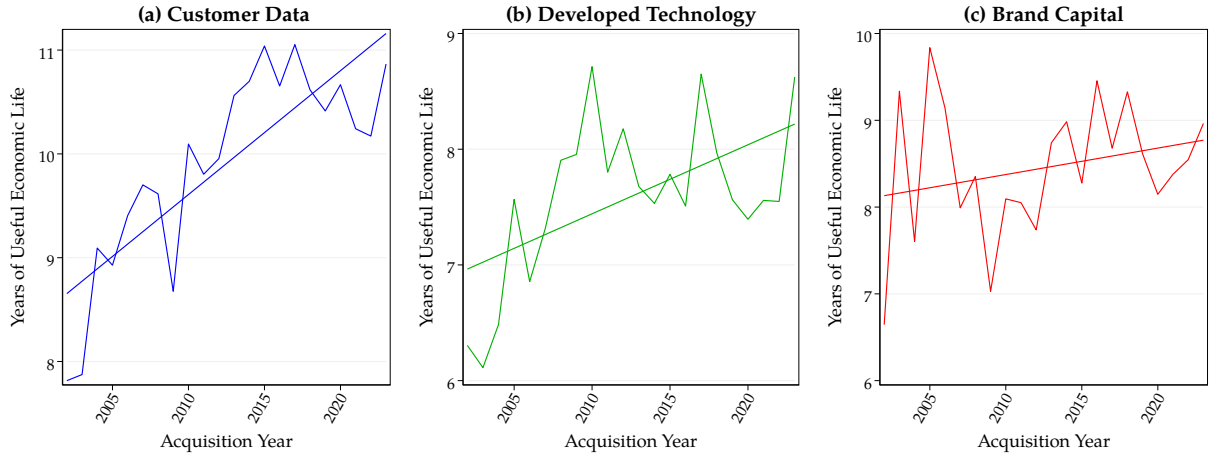


Figure 2.—Useful Life. These figures plot the means of useful life of acquired customer data (Panel A), developed technology (Panel B), and brand capital (Panel C) from 2002 to 2023. Data used to plot these figures are described in Online Appendix B.

Panel A displays a clear upward trend in the useful life of customer data, increasing from just under 8 years in 2002 to between 10 and 11 years beginning in 2012. Panel B shows that the estimated useful life of developed technology initially rises from 6.5 to 7.5 years, after which it generally stabilizes between roughly 7.5 and 8 years. Panel C focuses on brands. About 30% of brands are assigned an indefinite useful life by the acquirer, meaning

[12] Using a sample of purchase price allocations that included the purchase of identifiable intangible assets, He (2022) shows a rise in customer-related intangibles.

[13] In Supplemental Appendix F.1, we present a trends analysis at the sector level.

[14] The accounting standard ASC 350 requires firms to treat acquired in-process R&D as having an indefinite useful life, subject to impairment testing. Accordingly, we exclude it from these panels.

they will not depreciate in value unless impaired. For the remaining 70% that are assigned a finite life, the average useful life is between 8 and 9.5 years. Finally, in Supplemental Appendix E.1, we document a positive and statistically significant relationship between useful life and valuation. An additional year of useful life increases the average values of customer data, developed technology, and brand capital by approximately $19 million, $8 million, and $12 million, respectively.

4. Relation between Intangible Capital and Output

In this section, we build on the descriptive evidence in Section 3, which highlights the economic importance of intangible assets, and estimate the contribution of intangible capital to firm production. Our empirical analysis focuses on a subsample of transactions involving U.S. publicly traded target firms.[15] By combining PPA-based valuations at the acquisition date with firms' pre-acquisition measures of inputs and output, we overcome key measurement challenges that have constrained prior research and obtain more accurate estimates of output elasticities.

Although PPAs report asset values rather than physical quantities, they serve as proxies for productive capital, particularly for otherwise unobservable intangibles. Moreover, because PPA valuations reflect prices that would be received in orderly market transactions, they approximate value in use and thus align with the neoclassical view that capital enters production through the flow of capital services rather than historical cost (Jorgenson, 1963; Hulten, 1979; Corrado et al., 2009).[16] Under this interpretation, PPA fair values provide a market-based snapshot of the target's productive asset base immediately before acquisition, which is consistent with the view that capital should be measured in terms of its service flow or economic value rather than historical cost (Jorgenson, 1963; Hulten, 1979; Corrado et al., 2009).[17] This interpretation provides a consistent, empirically grounded foundation

[15] Accounting data necessary to measure output and production inputs—such as revenue, cost of goods sold, and SG&A—are publicly available for listed firms through financial disclosures. Comparable information is generally not publicly available for private targets, which prevents constructing consistent measures of inputs and output for those firms.

[16] In the neoclassical framework of Jorgenson (1963), the relevant measure of capital enters the production function through the user cost of capital. What matters for production is therefore the value of capital services, not the asset's historical acquisition cost. PPA valuations map naturally into this structure: they provide a transaction-specific estimate of the price of capital, grounded in expected future cash flows and market participants' assessments at the time of acquisition. In this sense, PPA-based asset values correspond closely to the theoretical construct that governs optimal investment and capital demand in Jorgenson's model.

[17] As with any estimate, PPA values may also introduce measurement noise. Fair values reflect managerial

for mapping capital inputs into a production-function framework (Levinsohn and Petrin, 2003).

In the sections that follow, we describe our sample of public target firms, estimate output elasticities, conduct robustness analyses, and discuss the implications of our results.

4.1 Sample of Publicly Traded Targets

To be included in the sample of public targets, a firm must be a U.S. publicly traded company immediately prior to its acquisition, and the transaction must involve the acquisition of 100% of the firm's equity or assets. We exclude firms that meet these criteria but report zero or negative sales. The final sample, summarized in Table 2, consists of 1,169 public targets. Although these acquisitions represent only 5.6% of the nearly 21,000 transactions in our dataset, they account for more than 50% of the total acquired assets (including goodwill) over the entire sample period (i.e., \$8 trillion / \$15.5 trillion = 51.4%). Supplemental Appendix G.1 presents a list of thirty of the largest firms in our sample.

As shown in Table 2, manufacturing, finance, services, and utilities & transportation comprise roughly 91.6% of the sample and 91.6% of the total value of assets acquired. Of the \$1.5 trillion of identifiable intangible assets acquired, over \$800 billion belongs to the manufacturing sector. Notably, in this sector, the fair value of intangible assets (\$827 billion) exceeds that of tangible assets (\$562 billion), suggesting intangible capital plays an economically important role in manufacturing.

assumptions about expected cash flows and discount rates, which may be influenced by financial reporting incentives (Shalev et al., 2013). As a result, PPA valuations embed both true economic information and noise, which may attenuate estimated capital elasticities in our production-function specifications.

	(N)		($M)				
Sector	Targets	% Targets	Assets	Intangibles	Goodwill	Total Value	% Value
Manufacturing	393	33.62 %	562,414	826,565	667,685	2,056,664	25.79 %
Finance	387	33.11 %	3,013,484	139,009	256,647	3,409,141	42.75 %
Services	182	15.57 %	206,842	247,591	448,266	902,700	11.32 %
Utilities & Transportation	75	6.42 %	528,172	186,842	220,266	935,279	11.73 %
Mining	61	5.22 %	301,537	12,250	37,029	350,815	4.40 %
Retail Trade	28	2.40 %	42,592	69,006	85,319	196,917	2.47 %
Wholesale Trade	28	2.40 %	43,716	15,541	21,713	80,971	1.02 %
Construction	11	0.94 %	23,062	1,518	12,735	37,316	0.47 %
Agriculture	3	0.26 %	2,740	1,465	1,291	5,496	0.07 %
Public Administration	1	0.09 %	14	16	0	30	0.00 %
Total	1,169	100 %	$4,724,573	$1,499,803	$1,750,951	$7,975,328	100 %

Table 2.—Summary Statistics of U.S. Publicly Traded Target Firms. This table presents summary statistics for the sample of 1,169 mergers and acquisitions that include U.S. public-traded target firms. We present, by sector, the number of targets and the value of tangible assets, intangible assets, and goodwill, respectively.

4.2 Quantifying the Output Elasticities of Intangible Capital

To quantify the output elasticities attributable to labor, tangible capital, intermediate inputs, and intangible capital, we estimate a Cobb-Douglas production function using a log-linear specification:

$$y_{i,t} = \beta_1 m\&l_{i,t} + \beta_2 k_{i,t} + \sum_{n=1}^{5} \beta_{3,n} q_{i,t,n} + \gamma_j + \tau_t + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is the natural logarithm of gross revenue for firm i in sector j at time t. Our factors of production include the natural logarithm of intermediate inputs and labor ($m\&l$), capital (k), and intangible capital (q). We estimate a single coefficient on intermediate inputs and labor because few publicly traded firms disclose total wage expenses. In addition, because direct labor costs are embedded in cost of goods sold, it is not feasible to accurately construct firm-wide labor expenditures and isolate direct labor from other input costs. We therefore measure intermediate inputs and labor as the combined total of cost of goods sold and selling, general, and administrative expenses.[18]

For tangible capital, we use fair values from PPAs, which better represents their value in use than book value for physical assets. Intangible capital is captured through its five largest categories: customer data, developed technology, brand capital, in-process R&D,

[18]We do not exclude R&D expenditures from intermediate inputs because Glaeser et al. (2025) show that a substantial share (approximately 55%) of R&D spending reflects employee compensation, which we aim to retain in our measure of labor input.

and product rights. Finally, we include sector fixed effects to account for time-invariant heterogeneity and year fixed effects to account for differences across time. We deflate all variables to 2017 U.S. dollars and define them in Supplemental Appendix H; we cluster standard errors by year.

If intangible assets are an important input into production, we expect their share of output to be substantial. We can infer this by summing the coefficients on intangible capital (i.e., $\sum_{n=1}^{5} \beta_{i,t,n}$) and comparing the result to more traditional inputs, namely, capital, and materials and labor. Table 3 reports the estimates.

Dependent Variable:	(1) *ln(Revenue)*	(2) *ln(Revenue)*	(3) *ln(Revenue)*	(4) *ln(Revenue)*	(5) *ln(Revenue)*	(6) *ln(Revenue)*
ln(Intermediate&Labor)	1.068***	0.943***	1.103***	0.982***	1.088***	0.983***
	(10.33)	(11.82)	(10.30)	(12.18)	(10.49)	(11.70)
ln(Capital)	0.151*	0.141*	0.179**	0.171**	0.196**	0.177**
	(1.74)	(1.81)	(2.10)	(2.29)	(2.17)	(2.25)
ln(CustomerData)		0.0240**		0.0231***		0.0237***
		(2.48)		(2.90)		(3.20)
ln(DevelopedTechnology)		0.0581***		0.0573***		0.0560***
		(3.79)		(4.25)		(4.25)
ln(BrandCapital)		0.0235***		0.0253***		0.0229***
		(4.63)		(4.66)		(3.24)
ln(In-ProcessR&D)		-0.0714***		-0.0740***		-0.0738***
		(-3.09)		(-3.26)		(-3.19)
ln(ProductRights)		0.0118		0.0414		0.0764**
		(0.48)		(1.56)		(2.44)
Observations	1,168	1,168	1,168	1,168	1,133	1,133
Excluded Singletons	1	1	1	1	36	36
Adjusted R^2	0.509	0.555	0.548	0.591	0.560	0.600
Sector F/E	Y	Y	Y	Y	N	N
Year F/E	N	N	Y	Y	N	N
Sector-Year F/E	N	N	N	N	Y	Y

Table 3.—Intangible Capital and Output. This table presents regression results from Cobb-Douglas production functions in the log-linear form. Across all columns, we use a sample of 1,169 U.S. publicly-traded target firms. Reported coefficients are from estimates of Equation 1. In columns (1), (3), and (5), we report coefficients from regressions that exclude intangible assets and in columns (2), (4), and (6), we report coefficients from regressions that include the five largest categories of intangible assets. All variables are described in Supplemental Appendix H. We vary the inclusion of fixed effects as follows. In columns (1) and (2), we include sector fixed effects, in (3) and (4) we include sector and year fixed effects, and in columns (5) and (6) we include sector × year fixed effects. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Column 1 excludes intangible capital and shows that the combined intermediate–labor input accounts for 106.8% of output, while tangible capital accounts for 15.1%. Column 2 includes the five types of intangibles. The sum of the coefficients for customer data, developed technology, brand, and product rights is 0.117, which implies their share is

11.7% of output. Remarkably, this share is similar to capital's 14.1%, suggesting these four intangible assets comprise a meaningful fraction of output. The coefficient on in-process R&D is negative, which, as discussed in greater detail in Section 4.4, likely reflects the value of this intangible does not immediately translate into output.[19]

Columns 3 and 4 repeat the estimation with year fixed effects and show qualitatively similar results to columns 1 and 2. Columns 5 and 6 further include sector-by-year fixed effects to absorb unobservable sector-specific shocks within a given year. Although the sample size decreases by 36 observations due to instances with only a single observation within a sector-year, our estimates remain robust.[20]

Given the growing importance of intangible capital, we next investigate whether the factor shares of intangible inputs have increased over time. To test this, we split the sample at 2012, the midpoint of our study period, and re-estimate Equation (1). As reported in Supplemental Appendix J, the results are consistent with intangible assets becoming more important for output. Specifically, after 2012, the estimated coefficients for customer data, developed technology, brand capital, and product rights all increase in magnitude, while the coefficient on in-process R&D becomes more negative. Moreover, post-2012, the combined coefficients on customer data, developed technology, and brand capital rival that of tangible capital (0.22 vs. 0.24). Taken together, these findings indicate that intangible assets contribute to output at a scale comparable to traditional capital.

4.2.1. Customer Capital Share of Output

Given that Supplemental Appendix G.2 shows that customer data and brand capital are among the largest categories of acquired intangible assets, they are a natural focus of our analysis of output elasticities. If these are indeed the most valuable intangible assets, we expect them to receive a disproportionately large fraction of the firm's output. Brand capital can foster loyalty among customers (Bronnenberg et al., 2022), which can create search frictions for customers (Gourio and Rudanko, 2014; Allen et al., 2019) and enable

[19] In practice, the fair value of in-process R&D is typically estimated using an income approach, whereby expected future cash flows from the project are projected and discounted to present value.

[20] To assess the generalizability of our results beyond acquired firms, Supplemental Appendix I reports distributions of estimates from 1,000 random samples from Compustat. Our estimated coefficients on intermediate inputs and labor, and capital, are statistically similar to the respective means of the random sample. Although we do not observe intangible capital—and the capital coefficients rely on book values rather than fair values—the similarity in estimates suggests that the production functions of acquired firms are not dramatically different from those of the broader population.

firms to capture a greater share of the surplus. Customer data, meanwhile, allows firms to adjust production, focusing on goods that their data predicts are likely to be more profitable (Eeckhout and Veldkamp, 2022). Together, both forms of intangible capital contribute to firms' ability to profit from customer relationships (He et al., 2024).

Table 3, column 2, confirms the value of customer capital: customer data and brand capital each receive a share of about 2.4% of output, which totals to 4.8%. This amount rivals that of developed technology and is more than one-third of the share of physical capital. These results help explain why customer capital receives a disproportionate share of assigned value as it plays a central role in generating firm output.

Consistent with the growing importance of customer data shown in Figure 1(b), the results reported in column 4 of Supplemental Appendix J indicate that the output elasticities of customer data and brand capital increase substantially after 2012. Specifically, the elasticity of customer data is more than twice as large (0.0333 vs. 0.0155), while the elasticity of brand capital is nearly three times larger (0.057 vs. 0.0117) relative to the pre-2012 period.

4.3 Addressing Endogeneity in Input Choices

A central econometric concern in the analysis presented in Table 3 is endogeneity. If firms' input choices are correlated with unobserved factors that also affect output, ordinary least squares estimates of input coefficients may be biased. To address this concern, prior work commonly adopts the production-function estimators developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), which exploit firm-level panel data to control for unobserved, time-varying productivity shocks that influence input decisions. Because our specification includes intermediate inputs and labor, and capital, we implement the approach of Olley and Pakes (1996), which uses capital expenditures (CAPEX) as a proxy for unobserved productivity.[21]

In our setting, intermediate inputs and labor are observed over time, whereas market-based stocks of tangible and intangible capital inputs are only observed at the acquisition date. To apply panel-based production function estimators, we therefore construct short,

[21]The Levinsohn–Petrin approach uses intermediate inputs as a proxy for unobserved productivity. In our setting, intermediate inputs are a key regressor of interest, making the Levinsohn–Petrin estimator inappropriate because it would mechanically partial out the variation in intermediate inputs used to identify their coefficient.

firm-level panels by assuming that intangible and tangible capital remain fixed over the short run (e.g., one year). This assumption allows us to form two-year panels for each public target and to implement the Olley–Pakes (OP) approach with the Ackerberg–Caves–Frazer (ACF) correction to mitigate endogeneity concerns.[22] While limiting the analysis to two years per firm may reduce precision and widen confidence intervals, we conduct this exercise as a robustness check and report the results in Supplemental Appendix K.

Column (1) reports estimates from the baseline production function using the OP approach. In column (2), we include the five key intangible assets as state variables in the estimation and find coefficient magnitudes that closely match those reported in column (2) of Table 3.[23] In column (3), we re-estimate the same production function including intangible capital as control variables and find that the magnitudes of the estimated coefficients remain qualitatively unchanged. Overall, the similarity between estimates from an OP approach (with the ACF correction) and our estimates from Table 3 suggests that simultaneity between input choices and productivity are unlikely to drive our estimates.

4.4 Innovation and Output

Innovation is a key driver of economic growth (e.g., Romer, 1990) because it enables firms to replace older technologies with more advanced ones (e.g., Aghion and Howitt, 1992). Much of the effort to develop these new technologies is associated with research and development. But at first glance, the negative coefficient on in-process R&D in Table 3 appears to imply that research and development *reduces* output. This interpretation is misleading. As specified in Equation 1, output is measured using current revenue. Unlike developed technology or customer capital, in-process R&D is an intangible asset related to products that have not yet been brought to market. These assets do not generate immediate revenue, which results in seemingly low levels of short-term productivity (Brynjolfsson et al., 2021). This asymmetry—where firms incur R&D costs upfront but realize the associated benefits later—creates a temporal disconnect between investment and output.

[22] Although we assume that intangible input quantities remain stable in the short run, we allow their dollar values to vary over time by deflating all amounts to 2017 dollars.

[23] In the Olley–Pakes framework, we treat intangible capital as a state variable because intangible investments—such as R&D, software, and organizational capital—are accumulated over time and are subject to adjustment frictions, rendering them predetermined with respect to contemporaneous productivity shocks, analogous to tangible capital.

For more mature or stable firms, this disconnect is less consequential: past R&D efforts are paying off in the present while new investments generate benefits in the future, so the lagged and lead effects tend to offset each other in steady state. But for firms earlier in their lifecycle, a larger share of their R&D portfolio consists of projects that are not yet commercialized, making the gap between investment and measured output especially pronounced. Therefore, studies that do not distinguish between in-process and developed intangibles may understate the true contribution of intangibles to productivity.

4.5 Explaining Variation in Output

Having demonstrated that intangible assets are important inputs to production, accounting for a sizable share of output, we next ask which types of intangibles explain the most variation in firm-level productivity. Factor shares capture the average contribution of inputs to output through their marginal products, whereas explanatory power—as measured by the R^2—speaks to dispersion, that is, how much differences in a given input help account for variation in productivity across firms (Syverson, 2011). To explore this, we perform a univariate analysis, introducing each input into the production function one at a time and evaluating the resulting R^2. Table 4 reports the results.

Dependent Variable: *ln(Revenue)*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Intermediate&Labor)	1.108***						
	(26.87)						
ln(Capital)		0.557***					
		(7.24)					
ln(CustomerData)			0.131***				
			(9.63)				
ln(DevelopedTechnology)				0.0450***			
				(3.01)			
ln(BrandCapital)					0.130***		
					(9.89)		
ln(In-ProcessR&D)						-0.0958***	
						(-2.95)	
ln(ProductRights)							-0.0941**
							(-2.52)
Observations	1,169	1,169	1,169	1,169	1,169	1,169	1,169
Adjusted R^2	0.453	0.227	0.148	0.014	0.129	0.044	0.010
Sector F/E	N	N	N	N	N	N	N

Table 4.—Univariate Analysis of Intangible Capital and Output This table presents estimates of univariate regressions in the log-linear form. Across all columns, the dependent variable is the natural logarithm of revenue. We use a sample of 1,169 U.S. publicly traded target firms. All variables are described in Supplemental Appendix H. We exclude fixed effects. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Several findings stand out. First, the output shares for customer data and brand capital, as displayed in columns (3) and (5), increase more than five-fold relative to the estimates in column (2) of Table 3. Second, these two inputs also exhibit significantly greater explanatory power than any other intangible asset—R^2 of 0.148 for customer data and 0.129 for brand capital. In fact, customer data alone accounts for nearly 65% of the explanatory power of physical capital (R^2 of 0.148 vs. 0.227), while brand capital accounts for nearly 57% (R^2 of 0.129 vs. 0.227).

5. Market Value and Intangible Inputs

Our results so far indicate that firms' identifiable intangible assets are significant predictors of current revenue. However, intangible capital, such as in-process R&D, is also expected to yield future benefits. In our M&A setting, testing this forward-looking relationship is inherently difficult, since target firms are acquired and their subsequent financial performance is no longer observable. Even if post-acquisition data were available, it would be challenging to separate the effects of the acquisition itself from the continuation of pre-existing firm dynamics. A natural way to circumvent this limitation is to examine pre-acquisition market values. If current intangible assets are expected to generate future cash flows, those anticipated benefits should already be reflected in the target firm's market valuation as the discounted present value of those cash flows.

5.1 Market-to-Book vs. Market-to-Adjusted Book

We begin by testing to what extent the ratio of market value of equity to book value of equity (the market-to-book ratio) for our sample of public targets declines once identifiable intangible assets are incorporated into book value. If the market already prices these intangibles, the gap between market and book values should narrow when they are included. In Figure 3, we plot the median market-to-book and market-to-adjusted-book ratios over time. The resulting pattern aligns with the evidence in Figure 1, which shows the growing importance of intangible assets: the adjusted market-to-book ratio approaches or equals one in the latter half of our sample period, when intangibles account for a larger share of acquired assets.

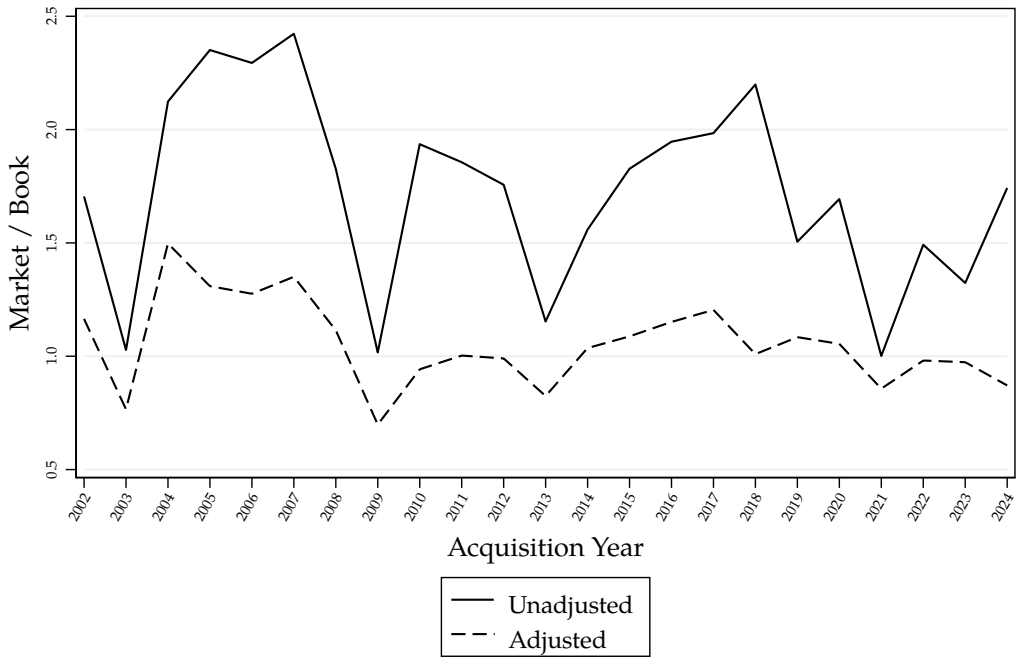


Figure 3.—Unadjusted and Adjusted Market-to-Book Over Time. The figure plots the median market to book ratio of our sample over time, with and without including value of acquired intangibles in the book value.

5.2 Relation between Market-to-Book Value and Intangible Capital

We next examine how variation in the market-to-book ratio relates to each of the main identifiable intangible asset categories. Specifically, we estimate the following regression model:

$$MTB_{i,t} = \sum_{n=1}^{5} \beta_{1,n} q_{i,t,n} + \gamma_j + \tau_t + \epsilon_{i,t}, \tag{2}$$

where $MTB_{i,t}$ is the natural logarithm of the unadjusted market-to-book ratio for firm i in sector j at time t. All other variables are as previously defined in Equation 1. Our sample is reduced from 1,169 to 943 observations due to data limitations on the total market value of equity.

Table 5 reports the results. Three key findings emerge from the main analysis presented in column (1). First, except for brand capital, all coefficients are positive and statistically significant, suggesting that variation in the market-to-book ratio is at least partially explained by identifiable intangible assets. Second, whereas our earlier results indicated that in-process R&D is negatively associated with current-period output, the relationship becomes positive in the forward-looking market-to-book regressions. This reversal is

consistent with the notion that markets capitalize the expected future returns from investments in technology, in line with evidence documented in prior research (e.g., Pakes, 1985; Austin, 1993; Kogan et al., 2017). Finally, coefficient magnitudes increase with the degree of investor transparency. Intangible assets that are more observable—such as product rights and developed technology, which are disclosed through contracts and patent grants—exhibit larger effects than less transparent assets like in-process R&D and customer data. In columns (2) and (3), we adjust our fixed effects structure, and find similar results.

Dependent Variable:	(1) *ln(MarketToBook)*	(2) *ln(MarketToBook)*	(3) *ln(MarketToBook)*
ln(CustomerData)	0.0115**	0.0102**	0.00884*
	(2.59)	(2.38)	(1.93)
ln(DevelopedTechnology)	0.0143**	0.0130**	0.01000*
	(2.36)	(2.34)	(1.82)
ln(BrandCapital)	0.00181	0.00282	0.00499
	(0.34)	(0.57)	(0.84)
ln(In-ProcessR&D)	0.00998*	0.0136**	0.0153***
	(1.76)	(2.39)	(3.18)
ln(ProductRights)	0.0303***	0.0350***	0.0328***
	(3.23)	(3.68)	(3.63)
Observations	944	944	908
Excluded Singletons	0	0	36
Adjusted R^2	0.158	0.210	0.271
Sector F/E	Y	Y	N
Year F/E	N	Y	N
Sector-Year F/E	N	N	Y

Table 5.—Market-to-Book and Identifiable Intangible Inputs. This table presents results from an ordinary least-squares (OLS) model that regresses logged market to book on intangibles. In columns (1) to (3) we include our five largest categories of intangible assets as in Table 3. All variables are described in Supplemental Appendix H. We include sector-level fixed effects in column (1). We include sector and acquisition-year fixed effects in column (2), and sector-year fixed effects in column (3). Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

6. Measured Productivity

Economists have long recognized that omitting relevant inputs from the production function leads to misattributing their contributions to total factor productivity (TFP).[24] Yet

[24]The notion that total factor productivity (TFP) may be biased dates back at least to Jorgenson and Griliches (1967). More recently, Corrado et al. (2022) contend that expensing rather than capitalizing intangible assets distorts our understanding of the sources of growth. Similarly, De Loecker and Syverson (2021) highlights that when intangible inputs are omitted from the production function, their contributions may be erroneously attributed to productivity.

despite this recognition, the measurement challenge remains largely unresolved in empirical work. Our findings thus far highlight the critical role of intangible assets in production, suggesting that their exclusion can significantly distort measured productivity—either by overestimating or underestimating true TFP.[25]

In this section, we examine how incorporating intangible assets into the production function influences measured TFP at both the firm and sector levels. We then identify which categories of intangible assets have the greatest effect, and assess how the inclusion of intangibles reshapes the dispersion of measured TFP. Finally, we consider how incorporating intangible assets in the production function impacts our understanding of TFP growth.

6.1 Quantifying TFP Changes

To study how including intangible assets in the production function affects measured productivity, we compute firm-level revenue-based TFP as the residual from Equation 1. We estimate TFP under two specifications: one that excludes intangible capital inputs and one that includes them. For each specification, we assign firms to deciles of the corresponding TFP distribution. We then construct the variable $DecileDifference$, defined as the change in a firm's TFP decile rank when intangible assets are included in the production function. This measure captures how accounting for intangible capital reshapes firms' relative productivity rankings.

Our results, shown in Figure 4, show how adjusting for intangible capital inputs affects measured TFP at the firm level. The impact is striking: nearly 70% of firms shift to a different TFP decile, leaving only about 30% in their original decile. While many firms move just one or two deciles, a sizeable 25% shift three or more deciles in either direction, and about 10.6% experience shifts as large as five to eight deciles. In terms of measured productivity, the mean absolute change in TFP following the adjustment is 1.27, representing a 69% shift relative to the average TFP of 1.852.

[25] True productivity may be underestimated when investments in new technologies take time before generating measurable output. If such lags are not incorporated into the production function, productivity estimates will be biased downward, an outcome Brynjolfsson et al. (2021) describes as the J-curve.

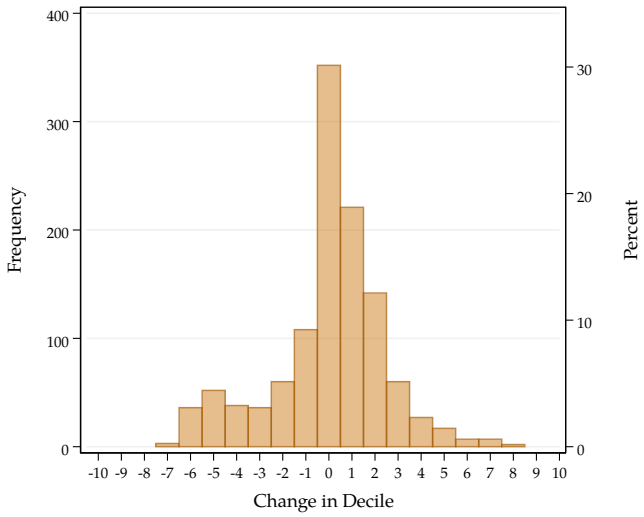


Figure 4.—Distribution of TFP Decile Changes in Target Firms. This figure presents the distribution of changes in TFP deciles after intangible assets are incorporated into firm-level production functions. Data to construct the histogram are reported in Table 6.

Extending the analysis to the sector level in Figure 5, we observe similarly large re-rankings. In manufacturing and services, for example, the mean absolute changes in TFP reach 3.01 (or 94%) and 0.627 (or 57.4%), respectively.

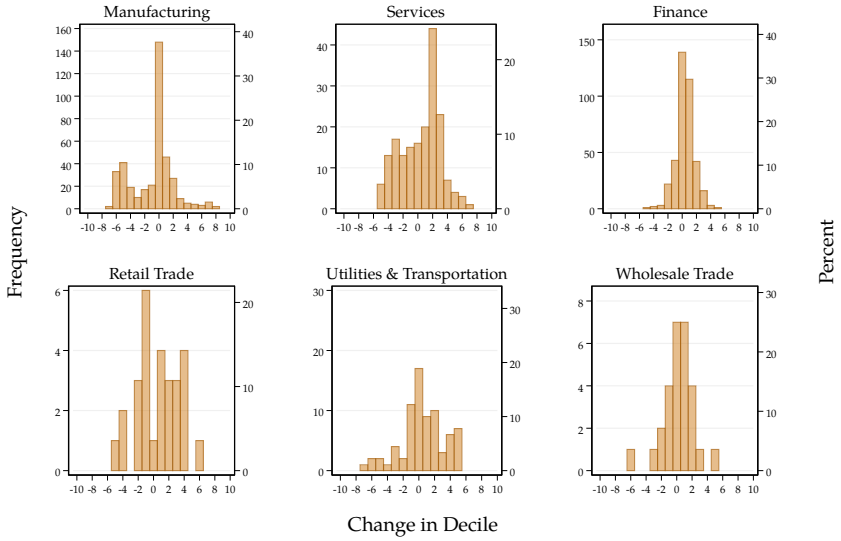


Figure 5.—Distribution in TFP Decile Changes in Target Firms by Sector. This figure presents the distribution of changes in TFP deciles, by sector, after intangible assets are incorporated into firm-level production functions.

To analyze where these shifts are concentrated, Table 6 reports decile changes by firms' initial decile rank. Reallocations occur throughout the distribution. In the bottom decile, 45% of firms move up by at least one decile, whereas in the top decile, 47% shift down

by at least one decile. Movement is even more pronounced in the middle. For instance, in the fifth decile, 88% of firms change their decile ranking. Overall, our results suggest that measured productivity is substantially biased when intangibles are excluded from the production function.

	Decile in Baseline Model										
DecileChange	1	2	3	4	5	6	7	8	9	10	Total
-7	0	0	0	0	0	0	0	2	1	0	3
-6	0	0	0	0	0	0	0	22	6	8	36
-5	0	0	0	0	0	3	19	9	9	12	52
-4	0	0	0	0	4	9	7	3	8	7	38
-3	0	0	0	8	5	7	4	6	1	5	36
-2	0	0	12	6	11	11	4	4	3	9	60
-1	0	24	9	12	18	7	7	6	11	14	108
0	64	23	26	16	14	31	33	30	54	61	352
1	23	21	24	35	30	25	22	17	24	0	221
2	18	22	19	17	19	12	17	18	0	0	142
3	2	8	11	15	11	9	4	0	0	0	60
4	3	7	6	6	2	3	0	0	0	0	27
5	2	4	8	1	2	0	0	0	0	0	17
6	1	5	0	1	0	0	0	0	0	0	7
7	3	2	2	0	0	0	0	0	0	0	7
8	1	1	0	0	0	0	0	0	0	0	2
Total	117	117	117	117	116	117	117	117	117	116	1,168

Table 6.—TFP Decile Changes Following Inclusion of Intangible Capital. This table presents decile changes of TFP. Measured TFP is obtained from a baseline model, which is shown in column (1) of Table 3, and then ranked in deciles. Measured TFP is obtained again after incorporating intangible assets in our baseline model, which is shown in column (2) of Table 3, and then ranked in deciles again. We then create a variable, *DecileChange*, which is the within-firm change in TFP decile ranking. All variables are described in Supplemental Appendix H.

6.2 Examining the Sources of TFP Changes

To better understand the direction of the bias in measured productivity, we build on the results from column (2) of Table 3 to design a new set of tests. We have found that customer data, developed technology, brand capital, and product rights all have positive effects on output, while in-process R&D is negatively associated. These findings imply that excluding the former group from the production function leads to overstated productivity, while excluding the latter results in understatement. Accordingly, the relationship between each intangible input and changes in TFP decile rankings should run in the opposite direction: including customer data, developed technology, brand capital, or product rights should be

linked to a decline in TFP decile rank, while including in-process R&D should correspond to an increase.

The results of the univariate regression analysis are shown in Table 7. With the exception of product rights, all coefficients align with the predicted directions, are similar in absolute magnitude, and are statistically significant. In economic terms, the coefficient on customer data in column (1) implies that a 1% increase in customer data is associated with a decline in TFP decile rank of over one-tenth of a decile. Applied to our sample, this suggests that moving from the 25th to the 75th percentile in customer data corresponds to an average decrease of 4.34 deciles in TFP rank. Similarly, the coefficient on in-process R&D (0.175) indicates that moving from the 25th to the 75th percentile corresponds to an average increase of 4.48 deciles in TFP rank.

Dependent Variable: *DecileChange*	(1)	(2)	(3)	(4)	(5)	(6)
ln(CustomerData)	-0.132***					-0.0527***
	(-17.57)					(-8.85)
ln(DevelopedTechnology)		-0.162***				-0.170***
		(-20.55)				(-11.75)
ln(BrandCapital)			-0.112***			-0.0284**
			(-10.19)			(-3.36)
ln(In-ProcessR&D)				0.175***		0.201***
				(14.28)		(14.27)
ln(ProductRights)					0.136***	-0.0507*
					(7.34)	(-2.29)
Observations	1,168	1,168	1,168	1,168	1,168	1,168
Adjusted R^2	0.259	0.276	0.184	0.237	0.090	0.595
Sector F/E	Y	Y	Y	Y	Y	Y

Table 7.—TFP Regressions. This table presents results from an ordinary least-squares (OLS) model that regresses change in TFP decile rankings on intangible assets. In Panel A, across all columns, the dependent variable, *DecileChange*, is a continuous variable that measures the change in TFP decile ranking. We present results from univariate regressions in columns (1) to (5), and results from multivariate regressions in column (6). All variables are described in Supplemental Appendix H.

6.3 Effects on the Dispersion of TFP

Prior research has consistently documented substantial heterogeneity in firm-level productivity within the same industry (e.g., Syverson, 2004; Hsieh and Klenow, 2009). Consistent with these findings, our baseline models reveal similarly large differences in TFP, as shown in Table 8. Panel A reports results for the full sample of public targets. The mean within-sector TFP is 1.852, with an interquartile range of 1.20. The 90–10 and 95–5

percentile differences are 2.91 and 3.87, respectively, closely aligning with prior studies. When we include intangible capital in the production function, these differences widen at the extremes: the 90–10 and 95–5 gaps increase by 0.40 and 1.00, representing 14% and 26% increases in TFP dispersion. Importantly, the mean TFP is statistically higher (0.501 or 27% higher) after adjusting for intangible inputs, indicating that accounting for intangibles in our sample leads to a mean-increasing spread in productivity outcomes on average.

Panel A. Overall Change in TFP Percentiles

	N	Mean	Median	SD	p5	p10	p25	p75	p90	p95
Baseline Model	1,168	1.852	1.202	4.238	0.363	0.562	0.836	2.037	3.468	4.237
With Added Intangibles	1,168	2.353	1.216	11.678	0.257	0.437	0.780	1.934	3.745	5.127
Difference		0.501***								

Panel B. Sector-Level Change in TFP Percentiles

	N	Mean	Median	SD	p5	p10	p25	p75	p90	p95
Manufacturing										
Baseline Model	393	3.181	2.569	6.748	0.002	0.425	1.683	3.507	4.720	5.579
With Added Intangibles	393	4.582	2.054	19.920	0.011	0.506	0.976	3.890	6.244	9.928
Difference		1.401*								
Services										
Baseline Model	182	1.093	1.058	0.436	0.485	0.609	0.818	1.336	1.631	1.749
With Added Intangibles	182	1.291	1.166	0.885	0.284	0.336	0.559	1.759	2.440	3.020
Difference		0.199***								
Finance										
Baseline Model	387	1.238	1.019	2.242	0.429	0.563	0.801	1.277	1.532	1.747
With Added Intangibles	387	1.191	1.117	1.028	0.317	0.510	0.837	1.333	1.498	1.865
Difference		-0.047								

Table 8.—TFP Percentiles and Intangible Capital. This table presents summary statistics of measured TFP. In Panel A, we present summary statistics of measured TFP for the full sample, where TFP is the de-logged residual obtained from regression estimates displayed in columns (1) and (2) of Table 3. The *'Baseline Model'* statistics are computed from residuals of a production function that excludes intangible assets; and the *'With Added Intangibles'* statistics are computed from residuals of a production function that includes intangible assets. In Panel B, we present the same summary statistics for three of the largest sectors in our sample. In both Panels A and B, we display the difference in means. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel B reports results at the sector level. In manufacturing, the effect of including intangibles is more pronounced than in the full sample. The interquartile range of TFP increases by 1.09 (60%), while the 90–10 and 95–5 percentile gaps expand by 1.44 (34%) and 4.34 (78%), respectively. These changes are driven entirely by firms in the upper tail of the TFP distribution; TFP at 90th and 95th percentiles increase by 32% and 78%, respectively.

Strikingly, we also find that mean TFP increases from 3.181 to 4.582, suggesting that unadjusted TFP underestimates productivity by roughly 44% on average in manufacturing.

In the services sector, we observe similar effects. The dispersion increases by 132% for the interquartile range, 106% for the 90–10 percentiles, and 116% for the 95–5 percentiles. These widening dispersions are also driven by the upper tail, as we find that mean TFP increases from 1.093 to 1.291 (18%). In contrast, TFP dispersion in the finance sector remains largely unchanged, and mean TFP in finance is not statistically different after adjusting for intangible capital.

To understand why TFP dispersion increases once intangible capital is incorporated into the production function, we test whether this reflects a re-ranking of firms driven by differences in intangible composition. Specifically, we examine whether firms with in-process R&D move up in the TFP distribution while firms with customer-related and developed technology assets move down. We partition the sample by the presence of in-process R&D and re-examine TFP at key percentiles after adjusting for intangibles. The results are reported in Table 9.

Panel A. Firms With Observed In-Process R&D

	N	Mean	Median	SD	p5	p10	p25	p75	p90	p95
Baseline Model	209	2.926	1.861	8.369	0.000	0.041	0.947	3.200	4.551	5.281
With Added Intangibles	209	6.809	2.579	27.083	0.000	0.303	1.561	4.360	9.049	15.050
Difference		3.883***								

Panel B. Firms With No Observed In-Process R&D

	N	Mean	Median	SD	p5	p10	p25	p75	p90	p95
Baseline Model	959	1.618	1.139	2.523	0.472	0.587	0.828	1.761	3.095	3.861
With Added Intangibles	959	1.382	1.115	1.265	0.288	0.440	0.729	1.494	2.507	3.723
Difference		-0.236***								

Table 9.—Explaining Changes in Dispersion. This table presents summary statistics of measured TFP. In Panel A, we present summary statistics of measured TFP for the sample of firms that have in-process R&D > 0. In Panel B, we present summary statistics of measured TFP for the sample of firms that have in-process R&D = 0. TFP is the de-logged residual obtained from regression estimates displayed in columns (1) and (2) of Table 3. The *'Baseline Model'* statistics are computed from residuals of a production function that excludes intangible assets; and the *'With Added Intangibles'* statistics are computed from residuals of a production function that includes intangible assets. In both Panels A and B, we display the difference in means. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A shows that firms with in-process R&D experience large upward revisions in TFP, consistent with these firms' productivity being understated on average. The increases

are substantial across the distribution: TFP at the 90th percentile nearly doubles from 4.551 to 9.049, and at the 95th percentile nearly triples from 5.281 to 15.050. In contrast, Panel B shows economically meaningful declines in TFP for firms without in-process R&D—firms that may have none, one, or multiple other types of intangibles that previously biased TFP estimates upward. After incorporating these intangibles into the production function, TFP falls at every key percentile. Taken together, the widening of TFP dispersion reflects two opposing shifts driven by heterogeneity in intangible assets: upward revisions for firms with in-process R&D and downward revisions for firms whose productivity was previously overstated.

6.4 Does adjusted-TFP better predict future growth?

Standard models of firm dynamics predict that firms with higher underlying productivity grow faster and invest more in innovation. However, when intangible inputs are excluded from the production function, measured TFP may embed the value of those inputs rather than true operating efficiency. Building on our earlier results, we therefore test whether adjusted TFP better captures firms' growth potential by comparing its predictive power for subsequent sales growth, sales per employee growth, and R&D investment growth to that of unadjusted TFP.

We focus on growth in the year preceding each merger. For every public target, we estimate both unadjusted and adjusted TFP at the beginning of the first full fiscal year prior to the transaction.[26] We then separately test the relationship between each growth measure and each TFP measure using the following OLS regression model:

$$Growth_{i,[t-1,t]} = \beta_1 TFP_{i,t-1} + \beta_2 TFP^2_{i,t-1} + \gamma_j + \tau_{t-1} + \epsilon_{i,t-1}, \tag{3}$$

where the dependent variable, $Growth_{i,[t-1,t]}$, is defined as the growth rate of sales, growth rate of sales per employee, or the growth rate of R&D investment for firm i, measured by the log-difference of the underlying variable of interest between periods t and *t-1*. The key explanatory variable, $TFP_{i,t-1}$, denotes either the natural logarithm of unadjusted or adjusted TFP measured at time *t-1*.

Panels A, B, and C of Supplemental Appendix N show the relationships between measured TFP (both unadjusted and adjusted) and our growth outcomes. The figures

[26] For example, if a firm was acquired midway through fiscal year 2016, we measure TFP at the start of fiscal year 2015 to ensure a complete year of pre-merger sales, sales per employee, and R&D investment data.

reveal nonlinear patterns consistent with models in which the relationship between productivity and growth is not monotonic. Motivated by this evidence, we allow for nonlinear associations in our regressions by including the squared term, $TFP^2_{i,t-1}$. In addition, the specification controls for sector fixed effects, to account for time-invariant differences across industries, and year fixed effects, to capture common shocks over time. Standard errors are clustered at the year level. All variables are expressed in 2017 U.S. dollars, with precise definitions provided in Supplemental Appendix H. We report the results in Table 10.

Panel A. Sales Growth						
Dependent Variable: $\Delta Sales$	(1)	(2)	(3)	(4)	(5)	(6)
ln(TFP)	-0.0151	0.188*	0.0294	0.235**	0.0569	0.259**
	(-0.13)	(1.91)	(0.23)	(2.12)	(0.41)	(2.20)
$ln(TFP)^2$	-0.0202	-0.00868	-0.0182	-0.00678	-0.0177	-0.00668
	(-1.41)	(-0.82)	(-1.24)	(-0.63)	(-1.17)	(-0.60)
Observations	1,150	1,150	1,150	1,150	1,115	1,115
Excluded Singletons	0	0	0	0	35	35
Adjusted R^2	0.114	0.113	0.113	0.117	0.083	0.089
Sector F/E	Y	Y	Y	Y	N	N
Year F/E	N	N	Y	Y	N	N
Sector-Year F/E	N	N	N	N	Y	Y
TFP Measure	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Panel B. Sales Per Employee Growth						
Dependent Variable: $\Delta Sales/Emp$	(1)	(2)	(3)	(4)	(5)	(6)
ln(TFP)	0.0645	0.128***	0.0689	0.139***	0.0819*	0.152***
	(1.65)	(3.31)	(1.56)	(3.17)	(1.95)	(3.03)
$ln(TFP)^2$	-0.0370***	-0.0359***	-0.0377***	-0.0393***	-0.0359***	-0.0417***
	(-3.60)	(-2.93)	(-3.53)	(-3.02)	(-3.54)	(-3.29)
Observations	1,095	1,095	1,095	1,095	1,060	1,060
Excluded Singletons	0	0	0	0	35	35
Adjusted R^2	0.066	0.055	0.069	0.061	0.085	0.082
Sector F/E	Y	Y	Y	Y	N	N
Year F/E	N	N	Y	Y	N	N
Sector-Year F/E	N	N	N	N	Y	Y
TFP Measure	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted

Table 10.—Adjusted TFP and Firm Growth. This table presents results from an ordinary least-squares (OLS) model that regresses measures of firm growth on TFP. In Panel A, the outcome is sales growth, $\Delta Sales$. In Panel B, the outcome is the growth of the ratio of sales to the number of employees, $\Delta Sales/Emp$. In Panel C, the outcome is the growth of R&D, $\Delta R\&D$. Across all columns, the dependent variable is defined as the growth rate of the outcome for firm *i*, measured by the log-difference in the outcome between periods *t* and *t-1*. The key explanatory variable, $TFP_{i,t-1}$, denotes either unadjusted or adjusted TFP measured at time *t-1*. In all columns, We include the squared term, $TFP^2_{i,t-1}$. All variables are described in Supplemental Appendix H. We vary the inclusion of fixed effects as follows. In columns (1) and (2), we include sector fixed effects; in (3) and (4) we include sector and year fixed effects; and in columns (5) and (6) we include sector × year fixed effects. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Table 10.—Adjusted TFP and Firm Growth (continued)

Panel C. R&D Growth						
Dependent Variable: $\Delta R\&D$	(1)	(2)	(3)	(4)	(5)	(6)
$ln(TFP)$	-0.0791	0.171*	0.0165	0.324***	-0.0948	0.192***
	(-1.01)	(2.00)	(0.18)	(3.54)	(-1.22)	(2.82)
$ln(TFP)^2$	-0.00433	0.0119**	0.00111	0.0211***	-0.00502	0.0132***
	(-0.91)	(2.08)	(0.22)	(3.70)	(-1.14)	(3.12)
Observations	477	477	477	477	445	445
Excluded Singletons	1	1	1	1	33	33
Adjusted R^2	0.618	0.619	0.617	0.622	0.539	0.541
Sector F/E	Y	Y	Y	Y	N	N
Year F/E	N	N	Y	Y	N	N
Sector-Year F/E	N	N	N	N	Y	Y
TFP Measure	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted

Panel A presents estimates from regressions of sales growth on TFP. In column (1), the coefficient on TFP is negative (-0.0151) but not statistically significant at any conventional level, implying no relationship between unadjusted TFP and sales growth. In column (2), where sales growth is regressed on adjusted TFP, the magnitude of the coefficient on TFP is positive (0.188) and statistically significant at the 10 percent level, consistent with the idea that adjusted TFP is a stronger predictor of future sales growth.[27] Similar results are shown in columns (3) and (4), which include year fixed effects, and in columns (5) and (6), which include sector-by-year fixed effects.

Panel B reports regression estimates of sales-per-employee growth on TFP. When using unadjusted TFP, we find no statistically significant relationship in columns (1) and (3). In column (5), which includes sector–year fixed effects, the estimated coefficient becomes positive and statistically significant at the 10 percent level. In contrast, the relationship between adjusted TFP and sales-per-employee growth, reported in columns (2), (4), and (6), is positive and statistically significant at the 1 percent level, with coefficients nearly twice as large as those in the unadjusted-TFP specifications.

Panel C presents estimates of R&D investment growth on TFP. Consistent with our other tests, we find no statistically significant relationship between R&D investment growth and unadjusted TFP, as shown by the negative coefficients presented in columns (1), (3),

[27]The difference between delogged TFP in columns (1) and (2) is approximately 51%.

and (5). However, columns (2), (4), and (6) reveal a positive and statistically significant relationship between R&D investment growth and adjusted TFP.

6.5 Adjusted TFP and Market Valuations

Although productivity is a key determinant of firm value in theory, it is difficult to observe in practice. We examine this in public equity markets where investors may conflate productivity with the value of intangible assets that are embedded in unadjusted TFP. Consistent with this possibility, our earlier market-to-book tests show a positive and statistically significant relation between valuation and identifiable intangible assets, suggesting that investors price intangible capital when valuing firms. However, if investors do not fully disentangle intangible inputs from productivity, then productivity measures that explicitly remove intangible capital may exhibit little or no relation with market valuation, even when they more accurately capture firms' underlying operating efficiency.

Table 11 presents evidence consistent with this view. In column (1), we estimate a univariate regression of market-to-book on unadjusted TFP with sector fixed effects, so that identification comes from within-sector variation across firms. We obtain a positive but statistically insignificant coefficient, suggesting that true operating efficiency is difficult for investors to observe and therefore difficult to price. Column (2) further explores this mechanism by jointly including the five key intangible inputs and adjusted TFP. The explanatory power of the model increases from 0.124 to 0.158, representing a more than 27 percent increase. However, while the intangible inputs are positively and statistically significantly related to market-to-book—which is consistent with our findings reported in Table 5—the coefficient on adjusted TFP weakens in magnitude relative to column (1) and remains statistically insignificant. Taken together, these results suggest that the insignificant relation in column (1) reflects the conflation of investor-valued intangible assets with operating efficiency, the latter of which appears largely unpriced. Columns (3) through (6) show that this pattern is robust to alternative fixed-effects specifications.[28]

Overall, we find no evidence that intangible-adjusted TFP is reflected in market

[28] Schoar (2002) documents a positive and statistically significant relationship between excess Tobin's Q and firm-level TFP among manufacturing firms from 1977 to 1995. One important distinction between our study and this prior work is that our analysis explicitly controls for firm-level intangible inputs, which we find are positively correlated with market values. Controlling for intangible capital is especially important for the manufacturing sector, as these inputs play a large role in production, as shown in Supplemental Appendix G.2.

Dependent Variable: *ln(MarketToBook)*	(1)	(2)	(3)	(4)	(5)	(6)
ln(TFP)	0.0251	0.0190	0.0111	0.00562	0.0161	0.0110
	(1.03)	(0.90)	(0.42)	(0.24)	(0.80)	(0.64)
ln(CustomerData)		0.0111**		0.0102**		0.00917*
		(2.52)		(2.38)		(2.02)
ln(DevelopedTechnology)		0.0136**		0.0123**		0.00940*
		(2.26)		(2.21)		(1.72)
ln(BrandCapital)		0.00214		0.00307		0.00491
		(0.39)		(0.61)		(0.82)
ln(In-ProcessR&D)		0.0109*		0.0147**		0.0162***
		(1.86)		(2.54)		(3.32)
ln(ProductRights)		0.0291***		0.0340***		0.0314***
		(3.09)		(3.47)		(3.38)
Observations	943	943	943	943	906	906
Excluded Singletons	0	0	0	0	37	37
Adjusted R^2	0.124	0.158	0.168	0.207	0.235	0.271
Sector F/E	Y	Y	Y	Y	N	N
Year F/E	N	N	Y	Y	N	N
Sector-Year F/E	N	N	N	N	Y	Y
TFP Measure	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted

Table 11.—Adjusted TFP and Market Valuation. This table presents results from an ordinary least-squares (OLS) model that regresses logged market to book on TFP. In columns (1), (3), and (5), the main variable of interest, $ln(TFP)$, is the logarithm of unadjusted TFP. In columns (2), (4), and (6), the main variable of interest, $ln(TFP)$ logarithm of adjusted TFP. In tests of adjusted TFP, we also include our five largest categories of intangible assets. All variables are described in Supplemental Appendix H. We include sector-level fixed effects in columns (1) and (2). We include sector and acquisition-year fixed effects in columns (3) and (4), and sector-year fixed effects in columns (5) and (6). Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively. Our sample is reduced from 1,169 to 943 due to missing market-to-book data.

valuations on average, consistent with investors' limited ability to disentangle operating efficiency from intangible capital and other unobservables using public information. This interpretation is reinforced by Figure 3: if equity markets priced intangible-adjusted TFP, augmenting book value with identifiable intangibles would lower the market-to-book ratio but would not, on average, drive it to one, since the remaining wedge would reflect the value of productivity. Yet our evidence, as shown in Figure 3, indicates otherwise.

6.6 Do acquirers pay a premium for productivity?

While market valuations reflect investors' perceptions of firm value in public equity markets, acquisition prices provide a distinct and potentially sharper setting in which

to assess whether productivity is priced. In M&A, acquirers must commit capital to acquire control of a target firm, and the deal premium reflects the value they assign to the target's expected future cash flows and synergies. Importantly, acquisition prices are formed after an extensive due diligence process, often lasting several months, during which acquirers obtain access to detailed, non-public information about the target's operations, technologies, and efficiency. This information advantage reduces reliance on market-wide signals and allows acquirers to more precisely assess underlying productivity. This setting therefore offers a unique opportunity to test whether TFP is priced by sophisticated buyers through the premium they pay above market price.

To examine the relationship between deal premiums and TFP, we estimate the following OLS regression model:

$$DealPremium_{i,t} = \beta_1 TFP_{i,t} + \beta_2 MarketValue_{i,t-1} + \beta_3 TFP_{i,t} \times MarketValue_{i,t-1} + \sum_{n=1}^{2} \beta_{4,n} Controls_{i,t,n} + \gamma_j + \tau_t + \epsilon_{i,t}. \quad (4)$$

where $DealPremium_{i,t}$ is defined as the premium paid for the common equity of firm i, and t is defined as the M&A announcement date. Following Eaton et al. (2021), we measure the premium as the difference between the offer price and the price at 105 trading days before the announcement date, all scaled by the price at 105 trading days before the announcement date. The key explanatory variable, $TFP_{i,t}$, denotes the natural logarithm of unadjusted TFP measured at time t. Prior literature shows that deal premiums are decreasing in the size of the target firm, so we include the logarithm of market value of total equity of the target measured at the end of the previous fiscal year before the merger announcement date. We also include an interaction between TFP and target market value to allow the valuation of productivity to vary with firm size, reflecting the possibility that the potential returns to buyers of larger and more efficient firms are likely smaller (Manne, 1965). We include a variable for the form of payment, and a variable for whether the deal is structured as a tender offer. We define these control variables in Supplemental Appendix H. Standard errors are clustered at the announcement-year level.

Table 12, column (1) presents the results. Unadjusted TFP is positively and statistically significant at the 10 percent level, indicating that higher unadjusted TFP is associated with higher deal premiums. However, interpreting the positive relationship between

unadjusted TFP and deal premiums is challenging, as unadjusted TFP embeds identifiable intangible capital, true efficiency, and other unobservables. We next employ a two-stage least squares (2SLS) model to examine whether the TFP-deal premium relationship we observe in column (1) is driven by the intangible-related component of the TFP. In the first stage, we regress the logarithm of unadjusted TFP on our five key intangible categories, market value, and controls. In the second stage, we take the residual of the first stage (i.e., TFP not explained by intangibles) and estimate Equation 4, substituting unadjusted TFP with the logarithm of the residual ($ln(UnexplainedTFP)$).[29] In results reported in column (3), we find that the part of unadjusted TFP not explained by intangibles is positively and significantly related to deal premiums. We also find an incremental improvement in the R^2 from 0.06 to 0.064, suggesting that the residualized measure accounts for additional cross-sectional variation in deal premiums.

[29] Although adjusted TFP is constructed as the residual from a production function that includes intangible inputs, our residualization of unadjusted TFP serves a different purpose. This decomposition isolates the component of that is predictable from observable intangible assets in the cross-section, allowing us to test whether the pricing of unadjusted TFP in acquisition premiums is driven by its intangible-related content rather than by operating efficiency per se.

Sample:	Full	Full (1st stage)	Full (2nd stage)	Full	ΔTFP<0	ΔTFP>0	ΔTFP<0	ΔTFP>0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DealPremium	*ln(TFP)*	*DealPremium*	*DealPremium*	*DealPremium*	*DealPremium*	*DealPremium*	*DealPremium*
ln(TFP)	0.249*			0.249**	0.582	0.202**	-0.161	0.253***
	(2.00)			(2.31)	(0.63)	(2.22)	(-0.25)	(2.83)
ln(UnexplainedTFP)			0.246**					
			(2.41)					
ln(MktValue)	-0.0613***	-0.0794	-0.0617**	-0.0604**	-0.0816**	-0.0527*	-0.0968**	-0.0185
	(-2.90)	(-1.63)	(-2.50)	(-2.45)	(-2.67)	(-1.75)	(-2.37)	(-0.43)
ln(MktValue)×ln(TFP)	-0.0148**			-0.0144**	-0.0228	-0.0115**	-0.000302	-0.0140***
	(-2.23)			(-2.57)	(-0.54)	(-2.36)	(-0.01)	(-2.92)
ln(MktValue)×ln(UnexplainedTFP)			-0.0142**					
			(-2.63)					
ln(CustomerData)		0.0148	-0.000441	-0.000640	0.00821	0.0000243	0.000590	0.000923
		(1.57)	(-0.19)	(-0.27)	(1.64)	(0.01)	(0.05)	(0.18)
ln(BrandCapital)		0.0163***	-0.000222	-0.000424	0.00619	0.000189	0.00316	-0.00243
		(2.86)	(-0.06)	(-0.11)	(1.30)	(0.03)	(0.46)	(-0.31)
ln(DevelopedTechnology)		0.0519***	-0.00404	-0.00434	0.00995	-0.0148	0.00696	-0.0177
		(3.89)	(-0.96)	(-1.02)	(1.67)	(-0.95)	(0.70)	(-1.18)
ln(In-ProcessR&D)		-0.0550**	0.0133**	0.0138**	-0.0145	0.0264*	0.0163	0.0340*
		(-2.77)	(2.33)	(2.45)	(-1.45)	(1.76)	(1.27)	(2.02)
ln(ProductRights)		-0.00861	0.00615	0.00542	-0.0115*	-0.00165	-0.0221***	-0.0121
		(-0.23)	(0.75)	(0.66)	(-1.92)	(-0.12)	(-4.80)	(-0.95)
TenderOffer	0.197**	-0.0807	0.194**	0.190**	-0.000964	0.372**	-0.0178	0.522**
	(2.41)	(-0.22)	(2.47)	(2.40)	(-0.01)	(2.58)	(-0.18)	(2.79)
AllStock	-0.0930	-0.171	-0.0831	-0.0896	0.0172	-0.159**	0.0310	-0.197
	(-1.56)	(-0.81)	(-1.45)	(-1.61)	(0.22)	(-2.34)	(0.24)	(-1.61)
Observations	980	980	980	980	445	533	227	263
Excluded Singletons	0	0	0	0	1	1	2	0
Adjusted R^2	0.060	0.073	0.064	0.064	0.030	0.115	0.022	0.162
Sector F/E	Y	Y	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N	N	N
TFP Measure	Unadjusted	Unadjusted	Unadjusted	Adjusted	Adjusted	Adjusted	Adjusted	Adjusted

Table 12.—Deal Premiums & Productivity. This table presents results from an ordinary least-squares (OLS) model that regresses deal premium on TFP. In column (1), the main variable of interest, $ln(TFP)$, is the logarithm of unadjusted TFP. In columns (2) and (3), we present results from 2SLS model, where in the first stage (shown in column (2)), we partial out the part of unadjusted TFP that is not explained by identifiable intangible assets; and in the second stage (shown in column (3)), we regress deal premium on the residual of the first stage—i.e., the residual of unadjusted TFP. In columns, (4) to (8), the main variable of interest, $ln(TFP)$, is the logarithm of adjusted TFP. In columns (5) to (8), we use subsamples as follows. In column (5), the sample includes firms whose TFP change from unadjusted to adjusted TFP is negative; in column (6), the sample includes firms whose TFP change from unadjusted to adjusted is positive. In columns (7) and (8), we reduce the sample even further to the firms whose TFP change was most negative (in (7)), and to the firms whose TFP change was most positive (in (8)). In tests of adjusted TFP, we also include our five largest categories of intangible assets, in addition to a set of controls ($TenderOffer$ and $AllStock$) that prior literature shows are generally correlated with deal premiums. All variables are described in Supplemental Appendix H. We include sector-level fixed effects in all columns in Panel A; sector-level and year-level, respectively, in Panel B.. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively. Our sample is reduced from 1,169 to 980 due to missing data on deal premiums

We next replace the logarithm of unadjusted TFP in Equation 4 with the logarithm of adjusted TFP and present the results in column (4). By removing the component of measured productivity attributable to identifiable intangible inputs, this specification tests whether acquirers pay higher premiums for operating efficiency per se rather than for intangible-related components embedded in unadjusted TFP. We find a positive and statistically significant association, at the 5 percent-level, between deal premiums and adjusted TFP.

We next ask how much of the variation in deal premiums explained by the full model is attributable to adjusted TFP, conditional on all other regressors and fixed effects. For this analysis, we estimate the model in column (4) excluding $ln(TFP)$ and the interaction term, $ln(TFP) \times ln(MktValue)$ and obtain the adjusted R^2. Removing these variables from the model reduces the adjusted R^2 from 0.064 to 0.055, indicating that approximately 15% of the variation in deal premiums is attributable to adjusted TFP and its interaction with market value.

Columns (5) and (6) report the results of a split-sample analysis designed to assess whether the relationship between adjusted TFP and deal premiums is driven by intangible-related mismeasurement. We divide the sample based on the sign of the difference between adjusted and unadjusted TFP. Firms for which adjusted TFP exceeds unadjusted TFP are those whose productivity is understated when intangible inputs are omitted. In column (6), we find that the positive association between adjusted TFP and deal premiums is concentrated entirely among these firms. By contrast, there is no evidence of a statistically significant relationship for firms whose unadjusted TFP overstates productivity, as shown in column (5). This pattern suggests that acquirers pay higher premiums only when measured productivity reflects genuine operating efficiency revealed after accounting for intangible inputs, rather than spurious productivity arising from mismeasurement.

Columns (7) and (8) extend this analysis by focusing on firms at the extremes of the distribution of the change from unadjusted to adjusted TFP. Specifically, we restrict the sample to firms with the most negative and most positive changes in TFP following the adjustment for intangible inputs. The results reinforce our earlier findings: the positive relationship between productivity and deal premiums is again concentrated among firms experiencing the largest upward revisions in TFP, with the effect strengthening further in

column (8). This pattern provides additional evidence that deal premiums are linked to TFP differences revealed after accounting for intangible-related mismeasurement.

7. Additional Analyses

In this section, we compare our results to expenditure-based approaches to estimating intangible capital, examine how accounting for intangible capital changes measured TFP growth, and explore the role of unidentifiable organizational capital in production.

7.1 Quantifying Output Elasticities using Expenditure-Based Estimates of Intangible Capital

Our findings based on the market values of identifiable intangible assets suggest that these assets play a significant role in production. However, market values are only observed in mergers and acquisitions, raising the question of whether commonly used expenditure-based estimates of firms' intangible capital stocks yield similar insights. In Supplemental Appendix L, we show that these estimates provide little explanatory power in production functions, do not explain market valuations, and generate far less resorting of TFP.

7.2 Examining Changes in Measured TFP Growth

In Supplemental Appendix M, we document a similar re-sorting of measured TFP growth when intangible capital inputs are incorporated into the production function. Excluding intangibles leads to systematic mismeasurement: productivity growth is understated for firms with above-median TFP growth and overstated for those with below-median growth. Consistent with this pattern, Supplemental Appendix M.5 shows that the gap between adjusted and unadjusted TFP growth remains positive for firms at the 75th and 90th percentiles and negative for those at the 25th and 10th percentiles throughout the sample period.

7.3 Unidentifiable Organizational Capital

A substantial body of research highlights that a firm's organizational capital, which is unidentifiable and therefore excluded from purchase price allocations (PPAs), is also economically significant (e.g., Atkeson and Kehoe, 2005; Bloom and Van Reenen, 2007; Corrado et al., 2009; Lev et al., 2009; Lustig et al., 2011; Carlin et al., 2012; Eisfeldt and

Papanikolaou, 2013, 2014). Organizational capital encompasses a wide range of firm-specific assets, such as the skills and experience embodied in employees or the firm's information about its personnel's capabilities (Prescott and Visscher, 1980). In this way, both the firm's shareholders and employees have claims to its cash flows. In Supplemental Appendix O, we estimate the output elasticity attributable to the unidentifiable organizational capital that is captured by the firm.

8. Conclusion

Although firms are increasingly investing in intangible capital, its role in production remains difficult to quantify because accounting rules typically exclude these assets from firms' balance sheets. We address this limitation using a novel dataset of nearly 21,000 corporate consolidations, which provide fair value estimates for thirty categories of intangible assets through purchase price allocations. We document that intangible capital—particularly customer data, developed technology, and brand capital—has grown substantially in economic importance over the past two decades, with identifiable intangibles now accounting for more than half of all acquired assets. These assets also contribute nearly as much to firm output as all tangible capital combined, implying that excluding them from the production function substantially distorts measured output elasticities and productivity.

Incorporating intangible capital meaningfully revises firm-level productivity estimates. Adjusting for these assets alters the relative productivity rankings of most firms and increases productivity dispersion within industries, reflecting heterogeneity in firms' intangible composition. Consistent with improved measurement of operating efficiency, intangible-adjusted TFP more strongly predicts firm growth. However, while this productivity measure is not reflected in public equity valuations—likely due to the limited observability of intangible assets—it is strongly associated with acquisition premiums in M&A transactions, where buyers obtain detailed information through due diligence.

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Supplemental Appendix to "Intangible Capital and (Mis)measured Productivity"

Appendix A. Sample Selection and Categories of Intangibles

A.1 Sample Selection

Our primary data come from U.S. publicly traded firms, which we focus on to ensure the availability of key information for our analysis. These data include detailed information on mergers and acquisitions—such as transaction dates, the names and locations of acquired corporations or assets, and their values. In particular, we use the values of acquired identifiable tangible and intangible assets, goodwill, and debt, manually extracted from Purchase Price Allocations (PPA) disclosed in firms' 10-K filings. Comparable data for private firms are not publicly available.

PPA disclosures are required under Accounting Standards Codification (ASC) 805, Business Combinations, which mandates that acquirers recognize identifiable assets acquired, liabilities assumed, and goodwill, generally measured at fair value as of the acquisition date. Goodwill equals the difference between the purchase price and the fair value of net identifiable assets.

This accounting standard was mandated by the Financial Accounting Standards Board (FASB) for acquisitions with dates beginning July 1, 2001. Accordingly, our sample includes M&A transactions with acquisition dates from January 1, 2002 through 2024.

Example of a PPA Disclosure

	October 13, 2015
Accounts receivable	$ 1,450
Inventories	682
Other current assets	166
Property and equipment	311
Intangible assets	46,200
Other assets	7
Total identifiable assets	$ 48,816
Accounts payable	$ 256
Accrued liabilities	1,589
Total liabilities assumed	$ 1,845
Net identifiable assets acquired	$ 46,971
Goodwill	69,871
Total consideration	$ 116,842

The valuation of the intangible assets acquired and related amortization periods are as follows:

	Valuation	Amortization Term (in years)
SUBTLE access technology	$ 2,179	5
IPR&D	44,021	
Total	$ 46,200	

A.2 Identifiable Intangible Assets

Notes: This table presents descriptions of intangible assets.

Intangible asset	Description
Customer data	Customer relationships, contractual or noncontractual; customer base; and customer lists.
Brand capital	Trademarks; trade names; and other brand assets.
Developed technology	Patented or unpatented innovations on products or services. Includes patents, core technology, existing technology, and manufacturing know-how.
Product rights	Exclusive rights to a product or process (e.g., pharmaceutical or healthcare).
In-process R&D	Intangible assets that are related to research and development activities.
FCC licenses	Federal Communications Commission broadcast licenses.
Franchise agreements	Contractual rights to operate a business under a specific brand or system.
Other intangibles	Undescribed intangible assets in PPA disclosures.
Other licenses	Undescribed licenses in PPA disclosures.
Distribution agreements	Contractual rights to distribute products.
Core deposit intangibles	Value of an acquired bank's or financial institution's core deposits. It represents the below-market source of funds from core deposits.
Non-compete agreements	Agreements that prohibit a person or business from competing with a company in a certain market for a specified period of time.
Order backlog	Unfulfilled purchase order contracts.
Software	Internally-developed software.
Assembled workforce	An existing collection of employees that permits an acquirer to continue to operate from the date of the acquisition.
Management agreements	Management contracts.
Supply agreements	Supplier agreements.
Referral network	Referral network(s) (e.g., physician referrals).
Royalty agreements	Right to receive future payments based on the use of intellectual property or other assets.
Trade secrets	Confidential information that creates a competitive advantage.
Database (not customer)	Database unrelated to customers.
Maintenance contracts	Maintenance and service contracts.
Power purchase agreements	Power purchase agreements.
Transmission system rights	Transmission system rights.
Pipeline capacity rights	Pipeline capacity rights that are below market value.
Rights to use	Telecommunication rights; land rights.
Lease intangibles	Value created from acquiring below-market leases.
Mineral interests	Legal rights to explore, extract, and retain mineral deposits.
Syndicate capacity	Intangibles related to syndicate capacity.
Contract rights	The value that arises from contractual agreements.

Appendix B. An Explanation of Useful Life Estimates

The useful economic life (or "useful life") of an intangible asset refers to the duration during which the asset is expected to contribute directly or indirectly to future cash flows. This period is estimated by the company that owns the asset, and the assessment depends on various firm-specific factors, some of which involve subjective judgment. In certain instances, a company may determine that an asset has an indefinite life, meaning there is no foreseeable limit to the period during which it is expected to contribute to the company's cash flows. An intangible asset should be regarded as having an indefinite useful life if no legal, regulatory, contractual, competitive, economic, or other factors impose a limit on its duration for the company.

For assets with a finite life, a firm should consider the factors listed in Accounting Standards Codification (ASC) 350-30-35-3 when determining the useful life of the asset. These factors include, but are not limited to, the expected use of the asset by the firm, the expected useful life of other assets to which the useful life of the asset may relate, legal or regulatory provisions that may limit the useful life, the impact of obsolescence, the effects of competition or other economic forces, and the level of maintenance required to obtain the expected future cash flows from the asset.

Appendix C. Other Data Sources and Sector Assignments

C.1 Other data sources

We supplement our intangible capital data with firm-level financial data obtained from Standard & Poor's Global Market Intelligence Compustat database. The Compustat database reports balance sheet and income statement data, sourced from 10-K SEC filings. We also rely on the Compustat database for firm-level SIC codes, which we use to assign firms to industries at the two-digit SIC level. To provide sector-level summary findings, we use the two-digit SIC codes to assign firms to one of ten sectors. Further details on this assignment process are described in Appendix C.2.

C.2 Sector Assignments

Notes: For our main analysis, we assign firms to sectors using two-digit SICs. We use the U.S. Department of Labor's Standard Industry Classification (SIC) Manual, which assigns firms into one of ten sectors.[30] The table below presents the mapping of SICs to these sectors.

Sector	**SIC (2-digit)**
Agriculture, Fishing, & Forestry	01, 02, 07, 08, 09
Mining	10, 12, 13, 14
Construction	15, 16, 17
Manufacturing	20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39
Utilities & Transportation	40, 41, 42, 43, 44, 45, 46, 47, 48, 49
Wholesale Trade	50, 51
Retail Trade	52, 53,54, 55, 56, 57, 58, 59
Finance	60, 61, 62, 63, 64, 65, 67
Services	70, 72, 73, 75, 76, 78, 79, 80, 81, 82, 83, 84, 86, 87, 88, 89
Public Administration	91, 92, 93, 94, 95, 96, 97, 99

C.3 Sample Distribution by Sector

Notes: This table presents the ranking, by number of mergers, of sectors. Note: Due to missing SICs, we are unable to assign 523 of the 20,963 deals to a sector.

Sector	Mergers	Percent
Manufacturing	6,766	33.1 %
Services	5,214	25.5 %
Finance, Insurance & Real Estate	3,914	19.1 %
Transportation, Communications, Electric, Gas & Sanitary Services	1,369	6.7 %
Retail Trade	900	4.4 %
Mining	883	4.3 %
Wholesale Trade	870	4.3 %
Construction	337	1.6 %
Agriculture, Forestry & Fishing	117	0.6 %
Public Administration	70	0.3 %
Total	20,440	100 %

Appendix D. Valuation Approaches in PPAs

The income approach is the most common method for valuing intangible assets. Within this framework, two common methods are widely used. The first is the multi-period excess earnings method (MPEEM), which is often applied to assets such as customer relationships or proprietary technologies. This method isolates asset-specific cash flows by deducting contributory asset charges, thereby capturing the net economic benefit attributable to the asset. The second is the relief-from-royalty method, which is often used to for trademarks or trade names. It estimates value by calculating the hypothetical royalty payments avoided by owning the assets rather than licensing them, thus imputing value from the cost savings.

The market approach infers fair value from observable transactions, relying on the principle that comparable market activity reveals investors' preferences. However, its applicability to intangible assets is limited due to the lack of active, liquid markets for most intangibles. By contrast, the approach is well-suited for assets with readily available market comparables, such as real estate or equipment, where sales data or transaction multiples (e.g., EBITDA or revenue) can be reliably obtained.

The cost approach estimates value based on the current cost to replace an asset, net of depreciation and obsolescence. It is best suited for assets that do not generate income or those that lack markets, such as internally developed software. For assets with clear income-generating potential, however, this approach is generally less informative as it relies solely on historical or replacement cost and therefore does not account for future economic benefits and expected returns.

In practice, acquirers typically engage valuation specialists to apply these methodologies across the acquired assets. Any excess of the total purchase price over the fair value of identifiable net assets is recorded as goodwill, which is intended to capture synergies or other residual sources of value that are not attributable to specific assets. Although goodwill is recorded on the balance sheet, our empirical analysis abstracts from it, focusing instead on the acquired components of tangible and identifiable intangible assets.

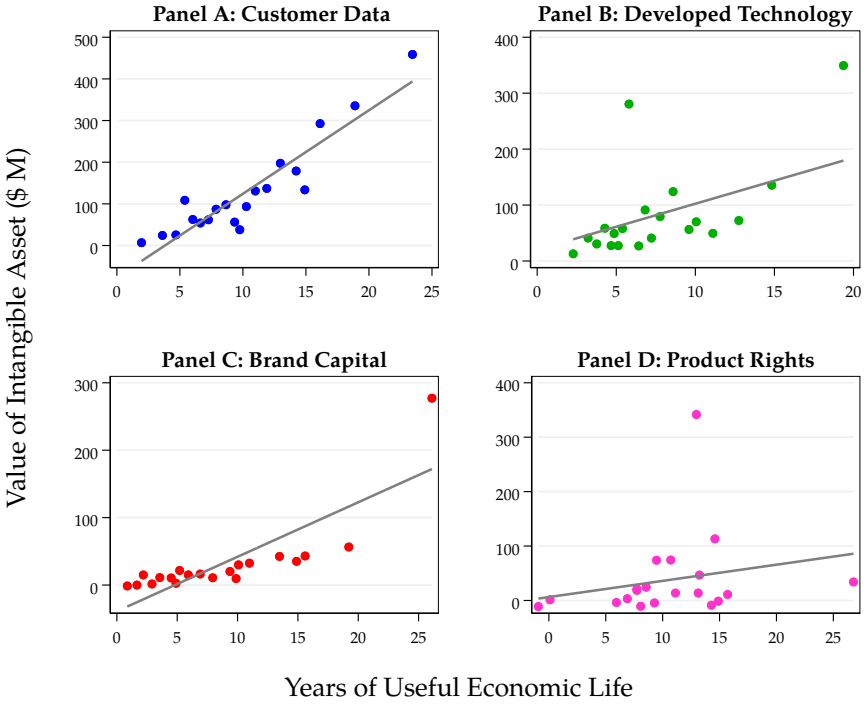
Appendix E. Useful Life and Intangible Asset Values

Our descriptive analysis of the useful life of key categories of intangible capital reveals several important patterns that enhance our understanding of their growing role in production. A central finding is that the useful life of these assets has generally increased over time. This raises a natural question: are the observed increases in asset values tied to the longer periods over which acquirers expect to benefit from them?

Intuitively, the value of an asset should be connected to the length of time an acquirer expects to use it. The figures in E.1 examine this relationship and show a clear positive relationship between the value of customer data (in Panel A), developed technology (in Panel B), and brand capital (in Panel C), and their useful life.

E.1 Relation between Fair Values and Useful Life

Notes: These figures plot the relationship between the fair value of customer data (Panel A), developed technology (Panel B), brand capital (Panel C), and product rights (Panel D) and their estimated useful life, respectively. We use Binscatter to generate the figures. As such, the dots represent the average outcome for a 'bin,' where bins are created automatically by the software program. The gray line is a "best fit" line. Fair values are in 2017 U.S. dollars.

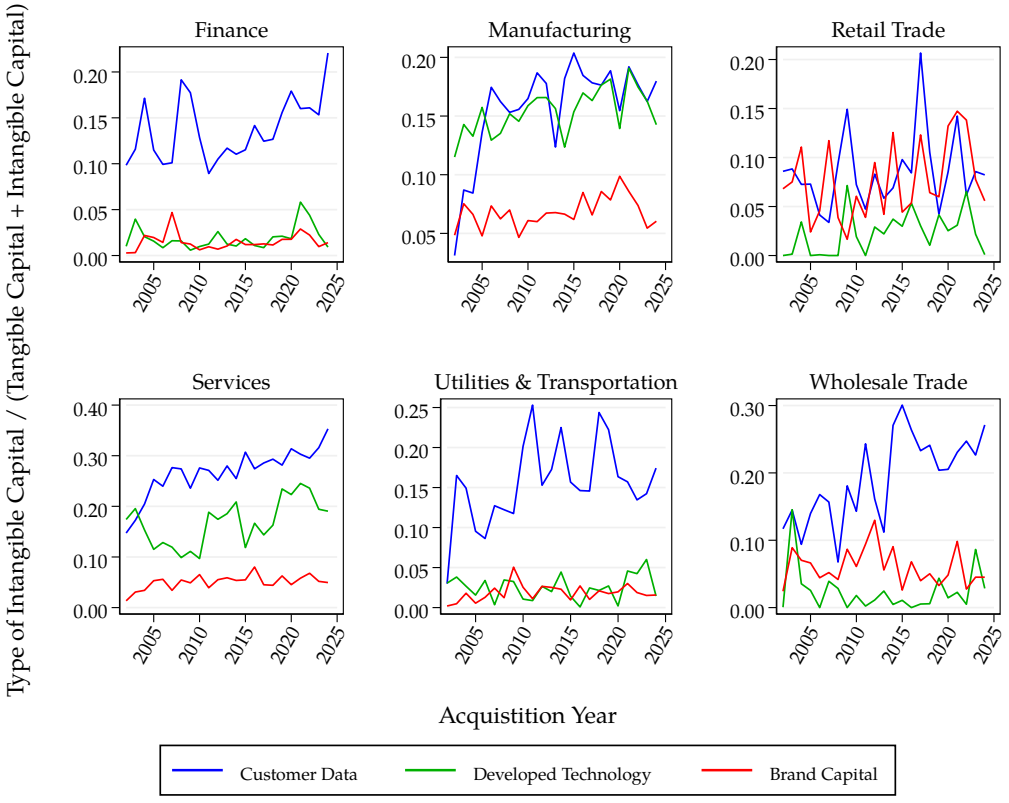


Appendix F. Sector Level Statistics

F.1 Proportion of Acquired Identifiable Intangible Assets

To put the aggregate patterns into context, the figures below break down trends by sector, focusing on three key categories: customer data, developed technology, and brand capital. These figures plot trends in the average ratio of each category relative to the total acquired intangible and tangible assets. Services and manufacturing, the two largest sectors, exhibit clear upward trends in customer data and developed technology. In the services sector, the proportion of acquired customer data more than doubled between 2002 and 2024, increasing from around 15% to 35%. Manufacturing exhibits an even steeper rise, climbing from 2% to 20%. The finance sector, which ranks third in M&A activity, also shows an increase in customer data, growing from 9% to over 20% since 2011. Other sectors display similar, though less pronounced, upward trends.

Notes: These figures plot, for the six largest economic sectors, the mean ratios of the value of acquired customer data, developed technology, and brand capital, respectively, to value of acquired tangible and intangible capital from 2002 to 2024. Data used to plot these figures are described in Supplemental Appendix A. Sectors appear in alphabetical order.



Appendix G. Publicly-Traded Targets

G.1 Acquisitions of U.S. Publicly-Traded Targets

Notes: This table presents a sub-sample of publicly-traded targets that are included in our full sample of 1,169 observations described in section 4.1. Acquisition year represents the year the merger was completed. Total assets is the sum of tangible assets, intangible assets, and goodwill, in billions of 2017 U.S. dollars. Data used to construct this table is described in section 3.1.

Acquisition Year	Public Target Firm Name	Sector	Total Assets ($B)
2019	SunTrust Banks, Inc	Finance	234.7
2018	Time Warner Inc	Util./Comm./Trans.	129.8
2004	John Hancock Financial Services	Finance	128.1
2017	DuPont	Manufacturing	116.6
2019	Celgene Corporation	Manufacturing	113.8
2018	Aetna Inc	Finance	111.1
2020	Sprint Corporation	Util./Comm./Trans.	95.1
2018	Express Scripts Holding Company	Retail Trade	94.7
2016	EMC Corporation	Manufacturing	89.4
2015	Kraft Foods Group, Inc	Manufacturing	86.2
2009	Schering-Plough Corporation	Manufacturing	77.3
2020	E*TRADE Financial Corporation	Finance	74.2
2020	TD Ameritrade	Finance	68.1
2010	Burlington Northern Santa Fe Corporation	Util./Comm./Trans.	66.5
2019	First Data Corporation	Services	65.3
2019	Worldpay, Inc	Services	58.7
2020	United Technologies Corporation	Manufacturing	58.9
2022	Xilinx, Inc	Manufacturing	55.1
2012	Progress Energy	Util./Comm./Trans.	49.9
2012	Medco Health Solutions, Inc.	Retail Trade	49.7
2006	Guidant Corporation	Manufacturing	35.4
2017	C.R. Bard, Inc	Manufacturing	31.9
2019	Total System Services, Inc	Services	31.3
2016	LinkedIn Corporation	Services	30.2
2021	Slack Technologies, Inc	Services	29.5
2018	L3 Technologies, Inc	Manufacturing	29.3
2008	Electronic Data Systems Corporation	Services	27.5
2016	Jarden Corporation	Manufacturing	26.9
2009	Rohm and Haas	Manufacturing	24.3
2013	Plains Exploration & Production Company	Mining	23.8

G.2 Summary Statistics of U.S. Publicly-Traded Target Firms

Notes: This table presents summary statistics for the sample of 1,169 mergers and acquisitions that include U.S. public-traded target firms. Panel A presents, by sector, the values of the five largest intangible asset categories. Panel B presents, by acquisition year, the number of targets and the value of tangible assets, intangible assets, and goodwill, respectively.

Panel A. Sector-Level Identifiable Intangible Assets

Sector	Customer data	Brand capital	Developed technology	In-process R&D	Product rights	Sum
Manufacturing	189,873	123,663	165,366	171,233	151,008	801,142
Finance	68,213	11,656	2,644	8	0	82,520
Services	137,855	23,114	60,754	5,594	0	227,317
Utilities & Transport.	29,729	22,985	1,761	0	0	54,475
Mining	3,077	833	1,049	127	0	5,086
Retail Trade	49,556	14,976	339	0	0	64,871
Wholesale Trade	11,656	3,428	86	0	0	15,170
Construction	391	538	514	0	0	1,443
Agriculture	177	192	710	386	0	1,465
Public Admin.	6	0	9	1	0	16
Total	$490,533	$201,384	$ 233,233	$177,348	$151,008	$1,253,505

Panel B. Year-Level Acquired Assets

	(N)		($M)				
Acquisition Year	Targets	% Targets	Assets	Intangibles	Goodwill	Total Value	% Value
2002	54	4.62 %	37,318	5,670	19,558	62,546	0.78 %
2003	47	4.02 %	14,096	3,395	8,532	26,023	0.33 %
2004	62	5.30 %	158,837	24,419	29,555	212,811	2.67 %
2005	51	4.36 %	87,435	14,513	33,560	135,507	1.70 %
2006	54	4.62 %	176,410	32,116	58,320	266,845	3.35 %
2007	63	5.39 %	53,739	30,467	46,427	130,633	1.64 %
2008	46	3.93 %	211,864	50,466	58,426	320,756	4.02 %
2009	34	2.91 %	716,024	58,414	42,213	816,652	10.24 %
2010	40	3.42 %	105,645	19,893	45,416	170,954	2.14 %
2011	37	3.17 %	104,990	28,160	35,864	169,014	2.12 %
2012	42	3.59 %	109,049	48,609	63,359	221,018	2.77 %
2013	45	3.85 %	137,336	8,925	21,861	168,122	2.11 %
2014	44	3.76 %	72,485	24,720	28,362	125,568	1.57 %
2015	65	5.56 %	154,224	132,503	134,292	421,019	5.28 %
2016	54	4.62 %	213,956	91,307	135,803	441,066	5.53 %
2017	58	4.96 %	166,748	85,071	135,004	386,822	4.85 %
2018	66	5.65 %	252,771	200,771	234,227	687,768	8.62 %
2019	62	5.30 %	454,090	152,604	168,917	775,611	9.73 %
2020	44	3.76 %	269,482	146,226	93,442	509,150	6.38 %
2021	58	4.96 %	278,422	54,687	80,160	413,269	5.18 %
2022	53	4.53 %	478,035	108,908	118,366	705,308	8.84 %
2023	50	4.28 %	245,675	112,009	112,858	470,542	5.90 %
2024	40	3.42 %	225,942	65,951	46,429	338,322	4.24 %
Total	1,169	100 %	$4,724,573	$1,499,803	$1,750,951	$7,975,328	100 %

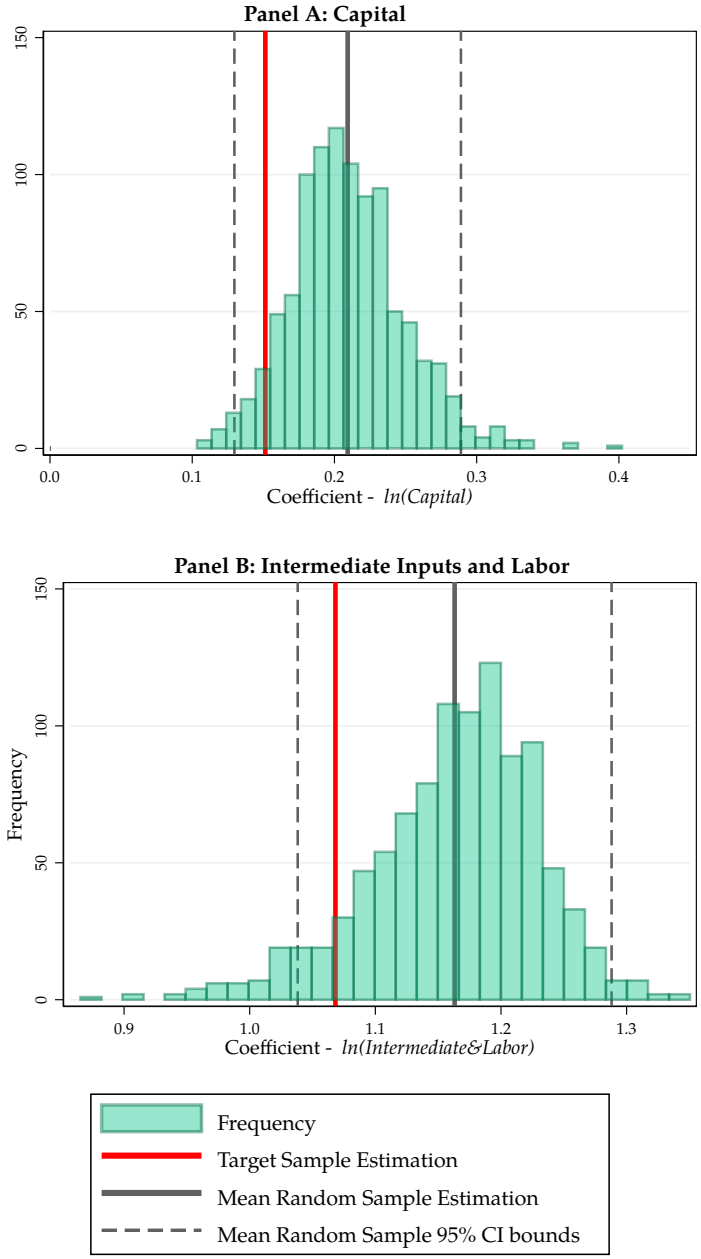
Appendix H. Variable Descriptions and Sources of Data

Notes: This table presents variable descriptions.

Variable	Description	Data Source
ΔTFP	Continuous measure of the change in de-logged TFP.	Our calculations
DecileChange	Continuous measure of the change in decile ranking of TFP.	Our calculations
DecileDecrease	Indicator variable that takes the value of 1 if the change in decile ranking of TFP is negative, and zero otherwise.	Our calculations
ln(Revenue)	Natural logarithm of gross revenue.	Compustat
ln(Capital)	Natural logarithm of tangible assets. Data obtained from PPA disclosures in 10-K SEC filings.	SEC EDGAR
ln(Intermediate&Labor)	Natural logarithm of SG&A plus COGS.	Compustat
ln(CustomerData)	Natural logarithm of the gross value of customer-related intangibles. Data obtained from PPA disclosures in 10-K SEC filings.	SEC EDGAR
ln(BrandCapital)	Natural logarithm of the gross value of brand-related intangibles. Data obtained from PPA disclosures in 10-K SEC filings.	SEC EDGAR
ln(DevelopedTechnology)	Natural logarithm of the gross value of technology-related intangibles. Data obtained from PPA disclosures in 10-K SEC filings.	SEC EDGAR
ln(In-ProcessR&D)	Natural logarithm of the gross value of in-process R&D-related intangibles. Data obtained from PPA disclosures in 10-K SEC filings.	SEC EDGAR
ln(ProductRights)	Natural logarithm of the gross value of products rights-related intangibles. Data obtained from PPA disclosures in 10-K SEC filings.	SEC EDGAR
UsefulLife	Useful life (in years) of intangible capital. We obtain data on the useful life of each category of intangible capital from 10-K SEC filings.	SEC EDGAR
ln(UnidentOrgCapital)	Natural logarithm of unidentifiable organization capital. Where unidentifiable organization capital is the replacement cost of organization capital from Peters and Taylor (2017) less customer data and brand capital from PPA disclosures.	SEC EDGAR
ln(KnowCapitalPT)	Natural logarithm of knowledge capital from Peters and Taylor (2017).	WRDS
ln(OrgCapitalPT)	Natural logarithm of organization capital from Peters and Taylor (2017).	WRDS
ln(OrgCapital)	Natural logarithm of organization capital derived from equation 5. Market value (mktvalt) obtained from Compustat. Assets, debt, and intangible capital obtained from PPA disclosures in 10-K SEC filings.	Compustat, SEC EDGAR
ln(MarketToBook)	Natural Logarithm of market to book ratio. Market value (mktvalt) and book value (ceq) obtained from Compustat. Measured at the end of the most recent fiscal year ending before the announcement date.	Compustat

Appendix I. Distribution of Factor Shares from Random Samples

Notes: This figure plots factor shares obtained from Cobb-Douglas production functions in the log-linear form. Each histogram contains coefficients obtained from 1,000 production functions estimated using random samples of firms in Compustat. Each sample contains 1,168 unique firms, matching the size of our sample of public targets. Panel A, Panel B, and Panel C, reflect the output share of labor, capital, and intermediate inputs, respectively. The red vertical line depicts our corresponding input share estimated in column (1) of Table 3; the gray dashed lines depict confidence intervals for the mean of the random samples.



Appendix J. Intangibles and Output over Time

Notes: This table presents regression results from Cobb-Douglas production functions in the log-linear form. We split our of 1,169 sample into two subsamples based on the year the deal was completed, *2012 and Before* and *After 2012*) and then repeat our analysis from columns (1) and (2) of Table 3. All variables are described in Supplemental Appendix H. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	(1) *ln(Revenue)*	(2) *ln(Revenue)*	(3) *ln(Revenue)*	(4) *ln(Revenue)*
ln(Intermediate&Labor)	1.020***	0.967***	0.905**	0.694**
	(13.33)	(11.27)	(2.92)	(2.74)
ln(Capital)	0.110*	0.111	0.274	0.240*
	(1.88)	(1.64)	(1.71)	(1.94)
ln(CustomerData)		0.0155**		0.0333**
		(2.45)		(2.29)
ln(DevelopedTechnology)		0.0147		0.0821***
		(1.15)		(4.07)
ln(BrandCapital)		0.0117***		0.0570***
		(3.60)		(4.21)
ln(In-ProcessR&D)		-0.0171		-0.109**
		(-1.22)		(-2.84)
ln(ProductRights)		0.00226		0.0473
		(0.10)		(1.00)
Time Period	Before 2012	Before 2012	After 2012	After 2012
Observations	584	584	583	583
Excluded Singletons	1	1	1	1
Adjusted R^2	0.696	0.704	0.415	0.505
Sector F/E	Y	Y	Y	Y
Year F/E	N	N	N	N

Appendix K. Alternative Specifications for Productivity

Notes: This table presents the results of estimates of production function parameters using the control function approach. Across all columns, the estimation is conducted on a panel of 1,078 firms with two firm-year level observations per firm. We assume the value of intangible assets remains stable in the year prior to the acquisition while adjusting for inflation. We estimate four specifications using the prodest command in Stata, applying Olley–Pakes (OP) procedures. We also include the Ackerberg–Caves–Frazer (ACF) correction throughout. As in Table 3, column (1) reports coefficients from regressions that exclude intangible assets; columns (2) and (3) report coefficients from regressions that include the five largest categories of intangible assets. All regressions include sector fixed effects. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable:	*ln(Revenue)*	*ln(Revenue)*	*ln(Revenue)*
ln(COGS)	0.917***	0.890***	0.878***
	(17.86)	(20.22)	(41.38)
ln(SG&A)	0.0858***	0.0909***	0.0694***
	(3.28)	(4.68)	(4.07)
ln(Capital)	0.0565	0.0492***	0.0460
	(1.44)	(2.67)	(1.45)
ln(CustomerData)		0.0457***	0.0275**
		(3.11)	(2.45)
ln(DevelopedTechnology)		0.0259	0.0215**
		(0.96)	(1.97)
ln(BrandCapital)		0.0221*	0.00347
		(1.77)	(0.27)
ln(In-ProcessR&D)		-0.0592	-0.0467*
		(-0.75)	(-1.89)
ln(ProductRights)		0.0718	0.0372*
		(1.57)	(1.86)
Observations	2,091	2,091	2,091
No. firms	1,078	1,078	1,078
Sector F/E	Y	Y	Y
Year F/E	N	N	N
Method	Olley-Pakes	Olley-Pakes	Olley-Pakes
ACF Correction	Y	Y	Y
Role of Intangibles	N/A	State	Control

Appendix L. Expenditure-Based Estimates of Intangible Capital

L.1 Quantifying Output Elasticities using Expenditure-Based Estimates of Intangible Capital

In this Supplemental Appendix, we ask: Do commonly used expenditure-based estimates of firms' intangible capital stocks yield similar insights to those of ours? The first indication that they may not is our finding that developed technology and in-process R&D exhibit opposing correlations with output, which is consistent with the productivity J-curve described by Brynjolfsson et al. (2021). These opposing effects imply that R&D capital must distinguish between early-stage, undeployed investments and fully developed innovations. The second indication lies with the wide variety of intangible asset types, each with useful lives that vary substantially across asset categories, time, and sectors. This heterogeneity makes identification and valuation difficult.[31] To assess how existing estimates compare to the market values of intangibles from PPAs, we examine whether the internally generated knowledge and organizational capital from Peters and Taylor (2017) (hereafter, PT) are associated with firm-level output.

Of the 1,169 public targets in our sample, we successfully match 1,056 (or 90%) to the PT dataset available through Wharton Research Data Services (WRDS). We use this matched sample to estimate three production function models, which we report in the table below. The first is a baseline model without intangible assets, identical to column (1) of Table 3. The second adds PT's estimated stocks of internally generated knowledge capital and organization capital. The third includes the fair value measures of firms' intangible asset stocks, identical to column (2) of Table 3.

The estimates from the production function that include PT's intangible capital measures, reported in column (2), yield three notable findings. First, the coefficient on *ln(OrgCapital)* is negative and significant, suggesting that higher levels of organization capital are associated with lower output. One interpretation is that *ln(OrgCapital)*, constructed from SG&A expenditures, mixes routine overhead with genuinely output-enhancing investments, making it difficult to isolate the component that should raise contemporaneous output—particularly for firms whose scale is changing. Another possibility is that organizational capital bundles investments that boost output immediately with others–such as employee training–that raise output only with a lag, a mechanism that matters primarily for firms that are expanding. Moreover, as shown in our analysis of useful lives, intangible assets linked to SG&A, including customer data and brand capital, vary widely in their useful lives, making it difficult to estimate capital stocks. Second, while the coefficient on *ln(KnowCapital)* is positive and statistically significant, it commingles early-stage research with developed technology, making it difficult to measure developed technology's share of current output. Finally, the inclusion of PT's intangible capital estimates adds little incremental explanatory power, as the change in the adjusted R^2 from column (1) to (2) is just 0.005.

Building on this comparison of production functions using PT estimates and PPA values, when we compare coefficients from column (2) to those in column (3) it is notable that the magnitude of the coefficient on *ln(DevelopedTechnology)* (5.82%) is more than double that of

[31] Consistent with this, He (2022) reports correlations between 0.16 and 0.48 when comparing the estimated intangible capital stocks based on prior literature to PPA valuations.

ln(KnowCapital) (2.81%) in column (2). Additionally, consistent with our results in Table 3, including the fair value estimates of key intangible assets increases the explanatory power of the model by a substantial 4.5 percentage points (or 9%), relative to that in column (1). Put differently, the increased adjusted R^2 in column (3) over that in column (1) is more than nine times that of the increase in column (2).

In column (4), we add *ln(UnidentOrgCapital)* to the specification in column (3) as a proxy for unidentifiable organizational capital. This measure is constructed by subtracting the fair values of customer data and brand capital from PT's estimate of internally generated organizational capital. The intuition is that if a portion of SG&A spending produces identifiable intangible assets—such as customer data and brand capital (e.g., He et al., 2024)—then the remaining share may capture unidentifiable organizational capital, including activities like employee training. This interpretation is consistent with Lev and Radhakrishnan (2005) and Peters and Taylor (2017), who treat SG&A as a broad proxy for organizational capital encompassing IT investments, training, brand enhancement, and spending on strategy consultants. Our construction therefore accommodates both identifiable components of organizational capital (e.g., customer relationships, brands) and unidentifiable components (e.g., firm-specific know-how).

The estimates in column (4) show that *ln(UnidentOrgCapital)* is negatively and significantly associated with output, with only a modest increase of 0.008 in the adjusted R^2. One explanation is that some SG&A-related investments—such as employee training—affect output only with a lag, a mechanism that would matter primarily if firms in the sample are growing at a meaningful pace. Another possibility is that PT's organizational-capital measure blends output-enhancing stocks (such as brand or customer-relationship improvements) with SG&A flows that do not reflect organizational capital at all—for example, executive compensation—thereby overstating the productive component of this asset.

L.1 Quantifying Output Elasticities using Expenditure-Based Estimates of Intangible Capital (continued)

Notes: This table presents regression results from Cobb-Douglas production functions in the log-linear form. Across all columns, we use a sample of 1,100 U.S. publicly traded target firms. Reported coefficients are from estimates of Equation 1. In column (1), we present our baseline model, which excludes intangible capital inputs. In column (2), we include estimates of the replacement costs of internally created intangible assets obtained from the Peters and Taylor (2017) dataset. Specifically, we include estimates of knowledge capital, *ln(KnowCapital)*, and organization capital, *ln(OrgCapital)*. In column (3), we include our intangible capital inputs. In column (4), we add *ln(UnidentOrgCapital)*, which is the unidentifiable organization capital. All variables are described in Supplemental Appendix H. We include sector-level fixed effects. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	(1) *ln(Revenue)*	(2) *ln(Revenue)*	(3) *ln(Revenue)*	(4) *ln(Revenue)*
ln(IntermediateInputs)	1.112***	1.102***	0.974***	0.966***
	(10.41)	(10.11)	(11.34)	(11.35)
ln(Capital)	0.124	0.113	0.122	0.0999
	(1.40)	(1.24)	(1.44)	(1.13)
ln(KnowCapital)		0.0281***		
		(3.07)		
ln(OrgCapital)		-0.0357***		
		(-3.17)		
ln(CustomerData)			0.0253**	0.0187**
			(2.34)	(2.13)
ln(DevelopedTechnology)			0.0582***	0.0652***
			(3.50)	(3.64)
ln(BrandCapital)			0.0223***	0.0121**
			(3.81)	(2.43)
ln(In-ProcessR&D)			-0.0707***	-0.0530**
			(-2.92)	(-2.14)
ln(ProductRights)			0.0156	0.0318
			(0.60)	(1.08)
ln(UnidentifiedOrgCapital)				-0.0541**
				(-2.63)
Observations	1,056	1,056	1,056	1,056
Excluded Singletons	0	0	0	0
Adjusted R^2	0.501	0.506	0.546	0.554
Sector F/E	Y	Y	Y	Y
Source of Intangible Inputs	None	P&T	PPA	PPA

L.2 Market to Book and Intangible Assets

In column (1), we report results from a specification that replaces the five key identifiable intangible assets with the organizational and knowledge capital measures from Peters and Taylor (2017). The evidence is mixed: organizational capital is positively and significantly associated with the market-to-book ratio, whereas knowledge capital is not. However, as noted earlier, prior studies construct organizational capital from SG&A expenditures, which often encompass spending on sales, advertising, and marketing activities that also contribute to customer and brand capital (Belo et al., 2014; He et al., 2024). To test whether the positive coefficient on organizational capital instead reflects these forms of customer-related intangibles, we subtract the values of customer data and brand capital from organizational capital and re-estimate the model. This specification includes our market-based measures of customer data and brand capital, the estimated value of knowledge capital, and the residual (unidentifiable) component of organizational capital.

Results from this analysis are shown in column (2). Consistent with our conjecture, the coefficient on customer data is positive and significant, with a magnitude comparable to those in columns (1) to (3) of Table 5. Brand capital again loads positively but remains insignificant, echoing our earlier findings in Table 5. Importantly, the coefficient on the residual organizational capital term becomes substantially smaller and statistically insignificant, suggesting that the positive effect observed in column (2) largely reflects the inclusion of customer-related intangible assets.

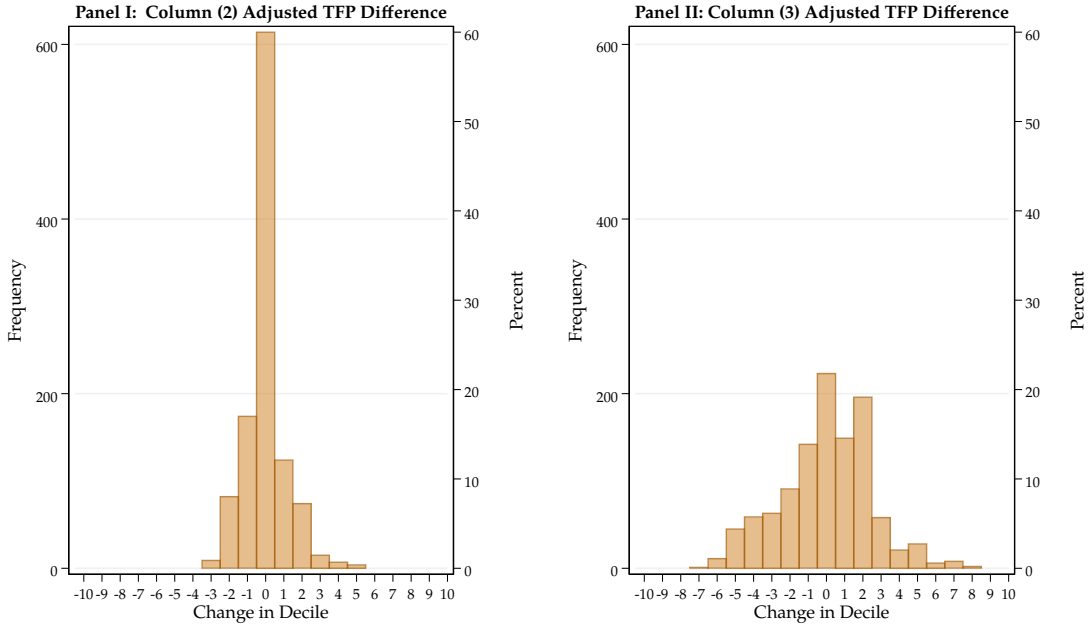
Notes: This table presents results from an ordinary least-squares (OLS) model that regresses logged market to book on intangibles and estimates of the replacement costs of internally created intangible assets obtained from the Peters and Taylor (2017) dataset. Specifically, in column (1) we include estimates of knowledge capital, *ln(KnowCapitalPT)*, and organization capital, *ln(OrgCapitalPT)*. In column (2), we include our intangible capital inputs *ln(CustomerData)* and *ln(BrandCapital)*, and add *ln(UnidentOrgCapital)*, which is unidentifiable organization capital. Variables are described in Supplemental Appendix H. We include sector-level fixed effects. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable: *ln(MarketToBook)*	(1)	(2)
ln(OrgCapital)	0.0216***	
	(6.02)	
ln(KnowCapital)	0.00671	0.00411
	(1.05)	(0.67)
ln(CustomerData)		0.0116**
		(2.69)
ln(BrandCapital)		0.00318
		(0.64)
ln(UnidentifiedOrgCapital)		0.00382
		(0.69)
Observations	938	938
Excluded Singletons	0	0
Adjusted R^2	0.140	0.132
Sector F/E	Y	Y
Year F/E	N	N
Sector-Year F/E	N	N
Source of Intangible Inputs	P&T	PPA, P&T

L.3 Distribution of Decile Changes

In this Supplemental Appendix, we compare TFP decile changes from production functions estimated in L.1. The figure on the left (Panel I) shows decile changes after expenditure-based estimates of intangible capital are included in the production function. The figure on the right (Panel II) shows decile changes after market values of intangible capital are included in the production function.

Notes: This figure presents the distribution of changes in TFP deciles after intangible assets are incorporated into firm-level production functions. Panel I plots the distribution changes between TFP estimates from columns (1) and (2). Panel II plots the distribution changes between TFP estimates from columns (1) and (3).



Appendix M. TFP Growth

M.1 Examining Changes in Measured TFP Growth

We next examine how incorporating intangible capital into the production function alters the distribution of TFP growth. A central challenge is that our sample consists of target firms, whose post-merger financial results are consolidated with those of the acquiring firms. To address this limitation, we measure TFP growth of our public targets in the year preceding the merger, when these firms were still reporting independently. We estimate TFP one year prior to the merger using the actual sales and intermediate inputs at that point in time. For the tangible and intangible capital inputs, we assume that they remain largely unchanged over such a short horizon, and thus use the market prices as of the acquisition date. In doing so, we also assume that any depletion of capital during that year is replaced roughly one-for-one, and that market prices for these assets remain stable on average in the short-run.[32] We follow prior studies and measure TFP growth as the difference in logged TFP.

The figure in Supplemental Appendix M.2 reveals that accounting for intangible capital in the production function significantly alters firms' TFP growth rankings: 61% of firms (705 out of 1,110) shift by at least one decile, and 15% shift by three or more. On average, the absolute change in TFP growth is 8 percentage points, more than three times the original mean of 2.5%. Supplemental Appendix M.3 further illustrates that while all major sectors experience some reordering, the shifts are especially pronounced in manufacturing and services.

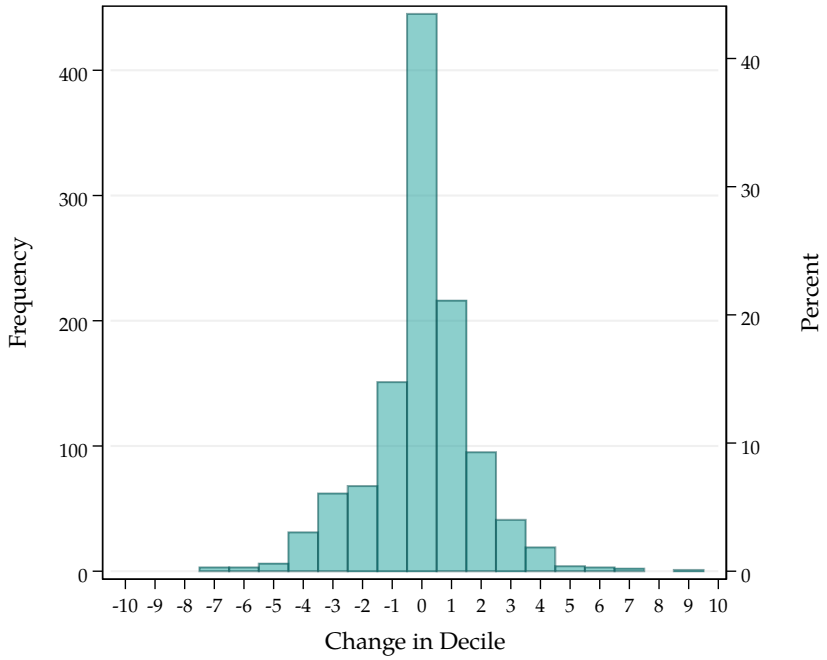
Supplemental Appendix M.4 reports the means and percentiles of TFP growth for the full sample and by sector. On average, adjusting for intangibles lowers mean TFP growth, from 0.025 to 0.019, but the effect varies across the distribution. For example, firms at the 75th and 90th percentiles exhibit higher TFP growth after the adjustment. In major sectors such as manufacturing and services, we observe a similar pattern, with 75th and 90th percentile firms showing gains in TFP growth after adjusting for intangibles. Moreover, these differences are economically significant.

Overall, our findings indicate that when intangibles are excluded from the production function, productivity growth is, on average, underestimated for firms with above-median TFP growth and overestimated for those with below-median TFP growth. Consistent with this, as shown in Supplemental Appendix M.5, the gap between adjusted and unadjusted TFP growth remains consistently positive for firms at the 75th and 90th percentiles, and consistently negative for firms at the 25th and 10th percentiles throughout the sample period.

[32] We lose 19 of the 1,169 public targets in our sample, due to data limitations.

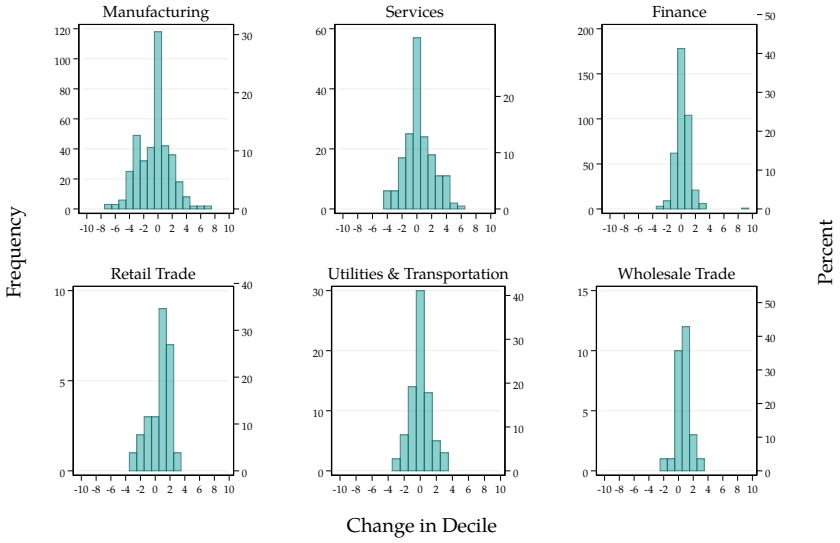
M.2 Distribution of TFP Growth Decile Changes

Notes: This figure presents the distribution of changes in TFP growth deciles after intangible assets are incorporated into firm-level production functions.



M.3 Distribution in TFP Growth Decile Changes by Sector

Notes: This figure presents the distribution of changes in TFP growth deciles, by sector, after intangible assets are incorporated into firm-level production functions.



M.4 TFP Growth Percentiles and Intangible Capital

Notes: This table presents summary statistics of measured TFP growth, where TFP growth is the difference in logged TFP. Logged TFP is the residual obtained from regression estimates using Equation 1. In Panel A, we present summary statistics of measured TFP growth for the full sample. The *'Baseline Model'* statistics are computed from a production function that excludes intangible assets; and the *'With Added Intangibles'* statistics are computed from a production function that includes intangible assets. In Panel B, we present the same summary statistics for six of the largest sectors in our sample. In both Panels A and B, we display the difference in means. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Overall Change in TFP Growth Percentiles

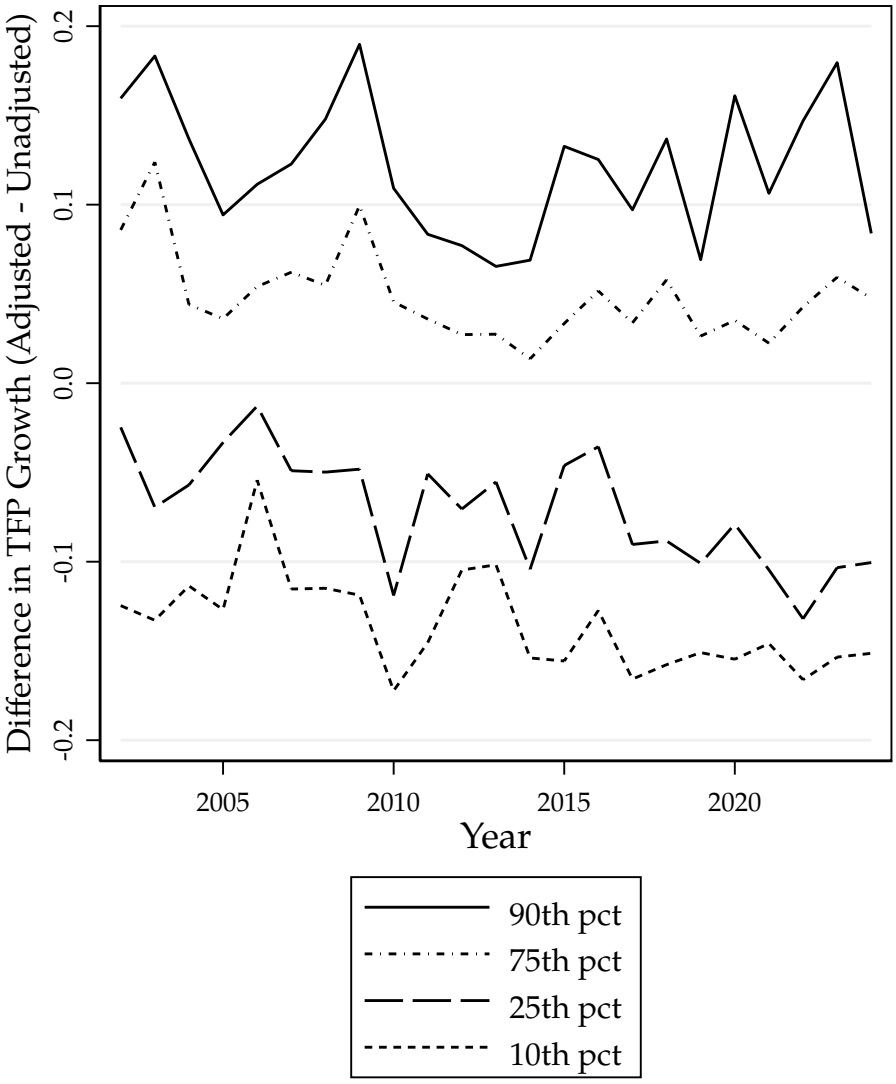
	N	Mean	Median	SD	p5	p10	p25	p75	p90	p95
Baseline Model	1,150	0.025	0.035	1.675	-0.515	-0.261	-0.064	0.096	0.193	0.348
With Added Intangibles	1,150	0.019	0.009	1.672	-0.497	-0.288	-0.108	0.114	0.233	0.362
Difference		-0.006*								

Panel B. Sector-Level Change in TFP Growth Percentiles

	N	Mean	Median	SD	p5	p10	p25	p75	p90	p95
Manufacturing										
Baseline Model	387	0.071	0.053	2.732	-1.049	-0.321	-0.018	0.103	0.253	0.584
With Added Intangibles	387	0.055	-0.008	2.729	-0.969	-0.351	-0.114	0.156	0.341	0.551
Difference		-0.016*								
Services										
Baseline Model	178	0.012	0.002	0.269	-0.329	-0.178	-0.059	0.071	0.153	0.317
With Added Intangibles	178	0.006	-0.002	0.311	-0.397	-0.250	-0.106	0.100	0.202	0.294
Difference		-0.007								
Finance										
Baseline Model	384	0.000	0.031	0.226	-0.321	-0.209	-0.082	0.102	0.192	0.311
With Added Intangibles	384	-0.000	0.025	0.215	-0.321	-0.218	-0.081	0.101	0.169	0.271
Difference		-0.001								
Retail Trade										
Baseline Model	26	-0.011	-0.007	0.046	-0.104	-0.074	-0.036	0.017	0.037	0.041
With Added Intangibles	26	-0.018	-0.022	0.076	-0.122	-0.109	-0.074	0.040	0.088	0.095
Difference		-0.006								
Utilities & Transportation										
Baseline Model	73	0.005	0.083	0.358	-0.311	-0.106	0.004	0.132	0.180	0.211
With Added Intangibles	73	0.008	0.094	0.370	-0.282	-0.159	0.009	0.140	0.186	0.217
Difference		0.002								
Wholesale Trade										
Baseline Model	28	0.000	-0.007	0.085	-0.125	-0.095	-0.037	0.036	0.098	0.146
With Added Intangibles	28	-0.000	-0.003	0.095	-0.217	-0.121	-0.033	0.052	0.101	0.119
Difference		-0.000								

M.5 Difference in TFP Growth Estimations over Time

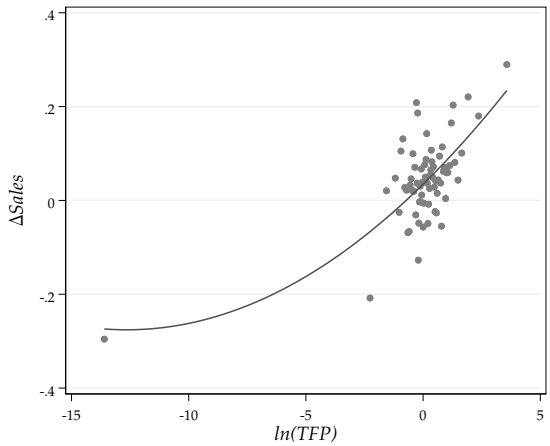
Notes: The figure plots the annual 10th, 25th, 75th, and 90th percentiles of the difference in TFP growth estimations with and without incorporating intangibles assets into the production function. We compute, by year, the within-firm change in TFP growth as the adjusted (with intangibles) TFP growth minus the unadjusted (baseline) TFP growth.



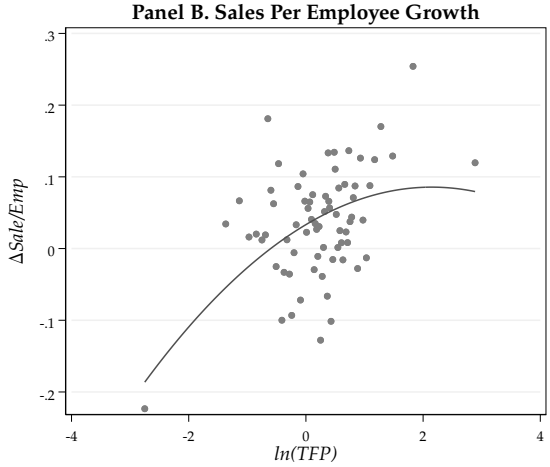
Appendix N. Relation of Growth Variables and TFP

Notes: These figures plot the relationships between our growth variables of interest and the logarithm of TFP. Panel A plots the relationship between sales growth and TFP; Panel B plots the relationship between sales per employee growth and TFP; and Panel C plots the relationship between R&D growth and TFP.

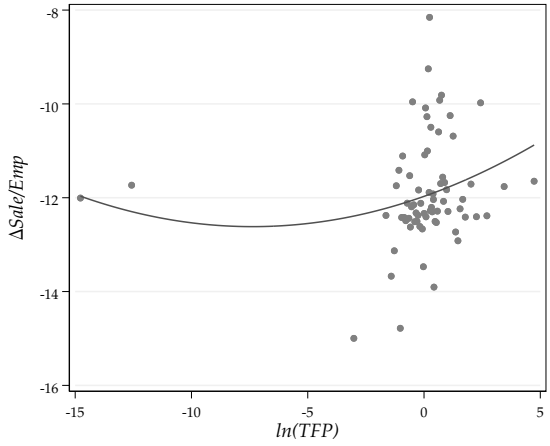
Panel A. Sales Growth



Panel B. Sales Per Employee Growth



Panel C. R&D Growth



Appendix O. Quantifying the Output Elasticity of Unidentifiable Organizational Capital

To estimate firms' unidentifiable organizational capital, we depart from the prior literature that estimates organizational capital stocks based on firms' SG&A expenditures (e.g., Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017). While SG&A captures some investments in unidentifiable organizational capital, these expenditures also reflect spending that maps into identifiable intangible assets—such as customer and brand capital—as well as other operating costs that do not generate organizational capital. Instead, we measure unidentifiable organizational capital as the residual component of enterprise value after subtracting the fair value of tangible and identifiable intangible assets, as follows:

$$OrgCapital_{i,t} = EnterpriseValue_{i,t} - Assets_{i,t} - IntangibleCapital_{i,t}, \tag{5}$$

where $EnterpriseValue_{i,t}$ represents the target firm's market value of total equity measured before the acquisition date plus the fair value of debt measured at the acquisition date. We measure the market value of total equity using end-of-fiscal-year market values computed one year prior to the merger, which helps avoid capturing stock price effects driven by expectations of the transaction itself, such as premiums reflecting anticipated synergies with the acquirer.[33] $Assets_{i,t}$ denotes the fair value of total tangible assets as of the acquisition date, and $IntangibleCapital_{i,t}$ refers to the fair value of identifiable intangible assets at that same date.

In the following table, we present estimates of Equation 1 that include organizational capital as an additional input. The sample size decreases from 1,169 to 1,049 observations due to missing data in Compustat. As shown in column (2), the coefficients on our five primary intangible assets remain similar in magnitude to those reported in Table 3. Consistent with the view that organizational capital enhances output, we find a positive and statistically significant coefficient (0.0231) on $ln(OrgCapital)$. This contrasts sharply with the negative coefficient obtained when using the SG&A-based measure of organizational capital reported in Supplemental Appendix L.1. Notably, the estimated coefficient on $ln(OrgCapital)$ is approximately one-quarter the size of the combined elasticities of the other intangible inputs, suggesting that the firm's revenue share that is attributable to unidentifiable organizational capital may be considerably smaller than previously assumed.

[33] Prior studies suggest that news leakage of the merger negotiations can lead to runups in the stock price well in advance of the announcement date. Such price runups will include expectations about future synergies and bidder competition, which we want to exclude from the analysis.

Notes: This table presents regression results from Cobb-Douglas production functions in the log-linear form. We include *ln(OrgCapital)*, as derived from Equation 5, and then repeat our analysis from Table 3. All variables are described in Supplemental Appendix H. Standard errors are clustered at the year level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively..

Dependent Variable:	(1) *ln(Revenue)*	(2) *ln(Revenue)*	(3) *ln(Revenue)*	(4) *ln(Revenue)*	(5) *ln(Revenue)*	(6) *ln(Revenue)*
ln(Intermediate&Labor)	1.099***	0.958***	1.129***	0.994***	1.131***	1.014***
	(10.66)	(11.02)	(10.53)	(11.15)	(10.38)	(10.40)
ln(Capital)	0.133	0.142	0.161*	0.168*	0.170*	0.167*
	(1.53)	(1.65)	(1.83)	(1.90)	(1.76)	(1.78)
ln(CustomerData)		0.0240**		0.0226**		0.0221***
		(2.29)		(2.45)		(2.81)
ln(DevelopedTechnology)		0.0506***		0.0513***		0.0504***
		(3.63)		(3.85)		(4.09)
ln(BrandCapital)		0.0243***		0.0258***		0.0234**
		(3.83)		(3.87)		(2.79)
ln(In-ProcessR&D)		-0.0665***		-0.0676***		-0.0671***
		(-3.22)		(-3.21)		(-3.05)
ln(ProductRights)		0.0134		0.0398		0.0751*
		(0.50)		(1.29)		(2.05)
ln(OrgCapital)		0.0231*		0.0139*		0.0176**
		(1.95)		(1.90)		(2.25)
Observations	1,049	1,049	1,049	1,049	1,016	1,016
Excluded Singletons	0	0	0	1	0	34
Adjusted R^2	0.503	0.548	0.541	0.581	0.550	0.588
Sector F/E	Y	Y	Y	Y	N	N
Year F/E	N	N	Y	Y	N	N
Sector-Year F/E	N	N	N	N	Y	Y