Do Digital Technology Firms Earn Excess Profits? An Alternative Perspective

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November 25, 2020

Abstract:

Regulators have alleged that digital giants (Alphabet, Facebook, Microsoft, Apple, and Amazon) have misused their market power to earn abnormal profits. Research that systematically documents whether technology firms earn abnormal profits is limited because (i) U.S. GAAP based accounting rate of return (ARR) expenses R&D and other intangibles; and (ii) ARR provides a single-period measure of performance that ignores the long-gestational payoffs associated with many of today's investments. We use a new measure of economic profitability, the internal rate of return (IRR), that equates long-term payback to current investments, inclusive of capitalized intangibles. We find, unlike for ARRs, increasing values of IRRs for technology companies over time, particularly for digital giants. Their IRRs range between 30% and 50% since 2008, which, coupled with the declined cost of capital, could point to abnormal profits. We provide an alternative perspective on technology firms' abnormal profits, which should likely interest regulators and policy makers.

Keywords: Internal rate of return; Economic profitability; Digital giants; Anticompetitive practices; Technology; Abnormal profits; Amazon; Google; Microsoft; Apple.

JEL Classification: D43, L1, M21, M41

We gratefully acknowledge comments from Bill Baber, Sudipta Basu, Sok Hyon Kang, Michael Mauboussin, Steve Penman, John Medrano, Jake Thomas, Ayung Tseng, and the workshop participants at University of Iowa and Columbia University's Accounting Design Project on earlier drafts. We thank our schools for financial support. All errors are ours.

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1. Introduction

Since the 2008 financial crisis, the number of firms entering or exiting different industries has declined (e.g., Gutiérrez and Philippon 2017) and the concentration of the largest firms in most sectors has increased (Autor et al. 2020). The technology industry is often cited as a poster child for this disturbing development. Regulatory authorities, particularly in the European Union, have alleged that digital giants, such as Alphabet (the parent company of Google) and Amazon, have misused their market power to engage in anticompetitive practices. Similar views were expressed by lawmakers in July 2020 during U.S. House Judiciary Committee hearings on the market dominance of the giant technology companies, namely Amazon, Apple, Facebook, and Google, and in the Department of Justice's (DOJ) antitrust case against Google.[1]

Central to the debate on concentration of market power is the potential to earn abnormal profits. However, research that systematically links such alleged concentration with increased profitability for technology firms is limited. Grullon, Larkin, and Michaely (2019) document that 75% of industries have experienced increased concentration in the last decades and that such concentration is associated with higher return on assets (ROA). The Council of Economic Advisers (2016) makes a similar point relying on a ratio of net operating profit after tax (NOPAT) to invested capital (measured as the sum of liabilities and the book value of equity minus goodwill). Loecker, Eeckhout, and Unger (2020) find that increased market power is associated with higher price markups over costs. These studies do not focus on technology firms partly because measuring their economic profits and price markups over costs is non-trivially difficult.

[1] See, e.g., https://www.nbcnews.com/tech/tech-news/break-big-tech-congressional-probe-idea-may-be-gaining-steam-n1235320 , https://www.justice.gov/opa/pr/justice-department-sues-monopolist-google-violating-antitrust-laws, and https://judiciary.house.gov/uploadedfiles/competition_in_digital_markets.pdf

The difficulty of measuring economic or abnormal profitability of technology firms arises because U.S. Generally Accepted Accounting Principles (GAAP) force firms to expense in-house research and development (R&D) and other intangible outlays in the calculation of profits. These outlays, reported as selling, general, and administration (SG&A) expenses, include investments in innovation, product development, process improvement, information technology, organizational strategy, hiring and training personnel, customer acquisition, and brand development, as well as in wringing efficiencies from firms' peer and supplier networks. Technology firms have vociferously argued for years that the mandatory expensing of internally created intangibles is inappropriate as such outlays create long-run advantages akin to investments in property, plant, and equipment (PP&E) but reduce current profits. If their argument held, a firm that earns large economic profits could still report huge losses as long as it makes value-added intangible investments.

Muddying the picture is a contrary claim that companies such as Amazon, Microsoft, and Netflix sell their products and services at below cost and, hence, are willing to incur large operational losses to eliminate competition. In such a case, a dominant technology firm's low profitability could be indicative of its predatory behavior. In either of two cases, the ROA or return on invested capital (ROIC) based on reported U.S. GAAP would not accurately represent the economic profitability of intangible investments in the technology sector.

We offer stylized evidence on the changes in firms' economic profitability of the technology sector over time using an alternative measure of economic profitability. We also present results for all industries to enable benchmarking. Our contribution is a method used to overcome the limitations of accounting rate of return (ARR; operating income after tax divided by reported total assets on the balance sheet) in measuring economic profitability. We estimate economic or internal rate of return (IRR), defined as the discount rate that equates investments with related operating cash flows following Fisher and McGowan (1983) and Baber and Kang (1996). In a seminal *American Economic Review* piece, Fisher and McGowan (1983) show that ARR (which is broadly ROA) is not a good proxy for economic returns for growth firms.

Consider Alphabet and Amazon. Their biggest investments, such as those in R&D, market development, and customer acquisition, are expensed as incurred, following U.S. GAAP. Such expensing not only reduces the numerator in the ARR calculation but also distorts the book value of the denominator (assets). Moreover, a single-period ARR inadequately measures profitability when the firm is best thought of as a portfolio of multiple projects in different stages of their life cycles. For instance, a company could be composed of multiple businesses, some of which have matured in terms of profitability (e.g., Alphabet's search engine and YouTube) and others have not yet been launched (e.g., Alphabet's Waymo car project). Furthermore, firms may be willing to discount sales prices to mitigate competition. In these cases, ARRs based on a single measurement period, with a mismatch between numerator and denominator, can be a misleading indicator for economic returns (Fisher and McGowan 1983).

We calculate IRRs by first computing a cash recovery rate each year, following the Baber and Kang (1996) evaluation of the economic profitability of the pharmaceutical industry, commissioned by the U.S. Congress's Office of Technology Assessment. Baber and King (1996), in turn, draws on the work of Ijiri (1978, 1979, 1980) and Salamon (1982, 1985). The cash recovery rate is constructed as cash payouts in a year divided by the amount of invested capital at the beginning of that year. To compute cash payout, we start with after-tax operating income and add back depreciation and amortization expenses, decreases in noncash working capital, and proceeds from the sale of invested capital, if any. We also add back the annual R&D spending along with 50% of SG&A (excluding R&D). This method mitigates the limitations of the U.S. GAAP by capitalizing R&D expenses (Fisher and McGowan 1983) and 50% of annual SG&A, consistent with recent research.[2] Invested capital is calculated by adding the running totals of the last five years' R&D and 50% of the last three years' SG&A (excluding R&D) to total assets. Unlike ARR, the total assets number in IRR is recalculated based on gross property, plant, and equipment, not depreciated values. The denominator in IRR thus represents the capitalized, un-depreciated values of assets that are potentially productive. For growing companies, R&D and SG&A capitalizations increase the numerator related to cash recoveries but also increase the denominator of invested capital.

More important, to overcome the single-period nature of the ARR, we make assumptions about the payback profile, that is, how long it takes to pay back an investment and what percentage of that payback occurs in each future period, following Salamon (1982). We then compute the implied IRR, or the discount rate that equates cash recoveries over the payback period to the initial investments.

We start with all firms covered by Compustat and the Center for Research in Security Prices (CRSP) between 1980 and 2019, a period that witnessed rapid technological changes. We retain firms with more than $100 million in inflation-adjusted assets (adjusted to year 2000), to focus on economically important firms (e.g., Dichev and Tang 2009). We then divide them into low-, stable-, and high-technology firms based on the first six digits of their Global Industry Classification Standard (GICS) codes using the definitions in Mizik and Jacobson (2013), Chandler (1994), and Chan, Martin, and Kensinger (1990). To a large extent, these classifications

[2] The literature uses varying percentages of SG&A (without R&D) to be capitalized. Eisfeldt and Papanikolaou (2013) and Falato, Kadyrzhanova, and Sim (2013) use 100%. Enache and Srivastava (2018) calculate this ratio at 43%, on average. Mauboussin and Callahan (2020) find that the portion exceeds 50% since 2000 (see https://www.morganstanley.com/im/publication/insights/articles/articles_onejob.pdf?1600268687963). Peters and Taylor (2017) use 30%. We use 50% for our base calculations and conduct a robustness test at 25%.

reflect low, medium, and high investments in R&D, respectively. For example, communications and information technology is classified as a high-tech industry, steel is classified as stable-tech, and forestry is classified as a low-tech industry. We isolate health-tech (biotechnology and pharmaceutical firms) from high-tech firms and label the remaining firms as the digital-tech sector. The current concern about the use of market size for anticompetitive practices primarily applies to digital technology companies. Accordingly, we separately examine the IRRs for digital giants, defined as digital-tech firms with market capitalization in excess of $500 billion as of October 30, 2020 (Apple, Microsoft, Amazon, Alphabet, and Facebook) to mirror regulatory and popular concerns that they pursue anticompetitive strategies and earn abnormal profits.

We begin our analysis by computing accounting rates of return from 1980 to 2019. We find that health-tech was the best-performing sector during the 1980s and 1990s. However, its dominance has petered out in the 21st century. From 2001 to 2018, low-tech has emerged as the best-performing sector, with relatively stable ARRs of about 12%. This is surprising given the popular perception that low-tech firms have struggled. At the very least, hardly anyone alleges that low-tech firms earn supernormal profits. Notably, digital-tech does not outperform any industry sector during any year and shows no evidence of abnormal profitability. Amazon, in particular, reports negative ARRs in its earlier existence and earns an ARR of less than 4% even in the 2010–2019 decade, during which time it allegedly exploited its dominant position in online retail market to indulge in anticompetitive practices. One may conclude that Amazon incurred losses, at least in the initial years, and continues to provide low-cost products and services to its customers.

IRRs, however, tell a different story. The health-high-tech group remains the best-performing sector during our entire study period of 1980–2019. But the digital-tech sector is the only cluster of firms that shows a positive trend in IRRs during the 21st century and has become equivalently the best-performing sector as health-tech sector since the 2008 financial crisis. Because cost of capital declined during the 21st century, primarily due to a fall in treasury yields, the gap between IRRs of the digital-tech firms and their cost of capital has dramatically widened. Furthermore, the digital-tech sector not only outperforms the low-tech and stable-tech sectors but also increases its margin of outperformance. The most notable outperformers are the digital giants. Since 2008, digital giants (Amazon, Alphabet, Microsoft, and Apple) report IRRs between 30% and 50%. Amazon's IRR in excess of 30% casts doubt on claims that it tolerates short-term losses to benefit consumers.

To put the high IRRs earned by digital giants in perspective, we compare them with the IRRs of 55 firms that were investigated by the Antitrust Division of the Department of Justice during our study period. We calculate the IRRs of the DOJ targets in the five years during and before the investigation. Their average, 13%, is significantly lower than IRRs shown by digital giants since the 2008 financial crisis. While the high IRRs per se may not trigger a DOJ investigation, our results show that considering IRRs, instead of ARRs, would lead to different conclusions if abnormal profitability is a potential cause for such an investigation.

We conduct an additional test using return on invested capital (ROIC) as a measure of performance.[3] To calculate ROIC, we add back to earnings an after-tax effect of net investments in intangible investments, which we calculate by subtracting the current depreciation of R&D and SG&A stock from the current intangible investments (R&D expenses and 50% of SG&A). The un-depreciated capital stock of R&D and SG&A is added to the denominator and cash holding is subtracted from total assets to obtain capital employed (IC). Similar to Ayyagari, Demirguc-Kunt, and Maksimovic (2020), we find higher ROICs for technology firms than their reported ARRs.

[3] Theory suggests that with restrictive assumptions, such as when growth rate equals IRR, ROIC could be an unbiased measure of IRR.

Ayyagari et al. (2020) use an unconventional measure of ROIC (based on highly specific assumptions such as ignoring corporate income taxes in the calculation of return and subtracting current liabilities and acquired intangibles from invested capital), which gives the appearance of supernormal returns for tech giants such as greater that 200% annual ROIC for Microsoft post-2008. Irrespective of conventional or unconventional adjustments in calculating ROIC, we argue that it suffers from the same limitations of ARRs, that is, a one-period snapshot of earnings weighted by an estimate of invested capital in that period as opposed to the multi-period perspective of IRR that we rely on.

One tentative interpretation for our findings is that the digital giants use their dominant positions to indulge in anticompetitive practices and earn abnormally high profits. Another interpretation is that technology firms have harnessed unprecedented innovation and productivity gains to reap large profits. We cannot distinguish which interpretation accounts for the high IRRs we document partly because obtaining reliable data on market shares in specific product segments and price-cost markups enjoyed by digital-tech firms is difficult (Basu 2019; Syverson 2019) (see Section 6.3).

We also admit that any yardstick of profitability, ARR or IRR, is admittedly dependent on assumptions. ARR is a one-period snapshot of performance that relies on the assumption that all of R&D and SG&A is an expense in that the benefit from such outlays expire in one accounting year. IRR is a multi-period cash recovery–based measure that treats R&D and 50% of SG&A as investments with useful lives of five and three years, respectively. Nevertheless, the relative rankings of firms are largely robust to assumptions about payback periods and alternative capitalization schemes (e.g., Salamon 1982, 1985; Lee and Stark 1987; Gordon and Hamer 1988; Griner and Stark 1988).

We conduct additional tests with alternative assumptions related to intangibles capitalization, payback periods, and payback profiles. The Spearman correlations between IRRs calculated using alternative assumptions exceed 95%, indicating at least that the same firms showing highest IRRs under one method also show highest IRRs under alternative methods. Even if these IRRs are overestimated by 100%, that is, their true values were 50% of what we find, they still exceed cost of capital by wide margins. Furthermore, IRRs (not ARRs) lead to similar conclusions as an analysis based on firms' Tobin's Q, a commonly used measure of abnormal profitability. Tobin's Q is more strongly related to IRR than ARR, particularly for technology firms in the 21st century.

We acknowledge an important limitation of IRR: It is affected to a greater extent by survival bias than is ARR because of the need for long time series data. This aspect is especially important for companies that make risky bets on technology. We observe only those that succeed with lottery-like payoffs, and not those that failed, portraying a potentially biased impression of R&D payoffs. We conduct an additional test to address the survivorship bias. We assume that the cash inflows upon delisting (merger) are zero (purchase consideration by the acquirer). The average IRR declines for all industries, but more so for health-tech (by approximately 2%) and digital-tech (1.5%). Nevertheless, our overall conclusions remain unchanged.

2. Institutional Background

2.1 Concentration and abnormal profitability in the technology industry

A review of the allegations against digital-tech firms motivates two sets of arguments. The case made by commentators and regulators such as the U.K. Competition and Markets Authority (Morton and Dinielli 2020) is that the digital giants such as Facebook and Google enjoy market shares of 40% or more.[4] Many economists, lawyers, and politicians argue that such large market concentration and the special nature of these companies' product markets, "such as network effects, economies of scale, data collection, tying of complementary goods, or operating online marketplaces—create unfair competition or insurmountable entry barriers" for new entrants (Bourne 2019, p. 1).

Consider Apple, which, in the early 2000s, transformed itself from a hardware company to a platform company. The music suppliers and consumers became tied to a common ecosystem linked around iPod and iTunes. Given the growing popularity of iPod and iTunes, more and more music companies caved in and joined the platform. Apple started taking a cut on each transaction going through its system, even though it never produced any music. As that ecosystem grew larger, consumers and suppliers were left with little choice but to continue to pay growing rents to Apple, to participate in that ecosystem. Apple extended that platform strategy by launching iPhone in combination with App Store. With each iPhone sale, Apple grew its ecosystem of consumers, attracting an ever-growing army of app producers, whose contributions nested within an iPhone made it an even more attractive product, drawing yet another fresh crop of new customers and app producers. The virtuous cycle kept repeating itself until a significant part of the market migrated and coalesced around Apple's iPhone network. App makers, such as the game company Epic, have challenged Apple's right to a large cut of their sales, 30% of gross revenues, and the regulators have taken notice.[5] Apple has retaliated by blocking new sales of Epic and its accessories from its game store. Epic has little choice but to comply with Apple's terms or miss out on the market of iPhone users.

[4] The full report issued by the U.K. Competition and Markets Authority is available at https://www.gov.uk/cma-cases/online-platforms-and-digital-advertising-market-study.

[5] See https://www.nytimes.com/2020/08/14/technology/apple-app-store-epic-games-fortnite.html.

Companies such as Apple whose profits grow with the size of the customer and supplier network and whose value could disappear rapidly with the loss of ecosystems would likely resort to anticompetitive behavior to maintain their control over the ecosystem. A potential rival that might grow a new ecosystem would be quickly acquired by the giants. For example, WhatsApp had the potential to compete with Facebook on the mobile telephone but was acquired by Facebook. The same fate was met by Instagram and numerous other start-ups in the social media industry. If rivals refuse to acquiesce, large tech companies can resort to cross-subsidization, predatory pricing, and bundling of their free products in a common suite. Examples include Microsoft's smothering of Netscape by bundling its "free" Internet Explorer and Amazon's dropping diaper prices in 2010 by as much as 30% to force an upcoming competitor, Diapers.com, to agree to be acquired.

The potential for anticompetitive practices of large companies can be illustrated by Amazon and Google. Amazon can exploit its increasing knowledge about its customers, their tastes, preferences, and urgency, to selectively price and bundle its diverse products and services in a common suite. More important, Amazon can demand (and it has demanded) preferred pricing and commercial terms from a supplier that has no choice but to comply with the terms and the fees asked for by a dominant platform. Thus, by controlling both the consumer and supplier ends of the equation, a dominant platform such as Amazon can effectively shut the competition out. Amazon also allegedly uses knowledge from sales patterns of small suppliers to improve its own competitive products.[6] Small firms that attempt to sell their products and services on a stand-alone basis have no chance of competing against a giant that bundles and cross-subsidizes its products.

[6] See https://www.cnbc.com/2020/04/23/wsj-amazon-uses-data-from-third-party-sellers-to-develop-its-own-products.html.

Google's alleged anticompetitive behavior is reflected in the fines that have been levied on it. In July 2017, European Union (EU) regulators fined Google $2.7 billion for allegedly abusing its search engine to prominently display product ads powered by its own services. In July 2018, EU regulators again hit Alphabet with about $5 billion in fines for bundling its search engine and Chrome apps into its operating system. In March 2019, Europe's antitrust regulators levied about $1.7 billion for freezing out rivals in the online advertising business. None of these cases against Google has met success in the courts. More recently, the U.S. Department of Justice has filed antitrust charges against Google.

One would expect that firms interested in preserving their market shares or abnormal profits, or both, would aggressively lobby regulators. Consistent with such expectation, in 2019 alone, Facebook spent $16.7 million on lobbying U.S. lawmakers.[7] Amazon and Alphabet are not far behind with lobbying expenditures of $16.5 million and $12.7 million, respectively.[8] These three firms feature in the top 15 spenders of more than 5,500 firms tracked by Open Secrets.org.

As of August 22, 2020, the price-earnings ratios of the digital giants range from high to astronomical. For instance, Alphabet trades at 35 times its earnings; Facebook, at 33; and Amazon, at 126. Hence, these digital giants are valued by investors as though their market shares are sustainable, and accumulation of data on their platforms will eventually allow these firms to reap substantial abnormal profits in the years to come.

2.2 The evolution of antitrust law

While little doubt exists that these technology giants have become dominant players in their fields, and numerous allegations have arisen about their anticompetitive behavior, whether

[7] See https://www.opensecrets.org/federal-lobbying/clients/summary?cycle=2019&id=D000033563. Data on lobbying of EU lawmakers are not readily available.
[8] See https://www.opensecrets.org/orgs/summary?id=D000023883

they have violated antitrust laws is unclear. For a long period of time, antitrust laws assumed that market concentration could harm consumers by enabling dominant firms to (i) indulge in price-fixing, market division, and tacit collusion; (ii) use their existing dominance to block new entrants; and (iii) exploit their bargaining power against consumers, suppliers, and workers, to hike prices and degrade service and quality while maintaining profits by way of predatory pricing. Regulators acted accordingly. For example, in the early 20th century, when Standard Oil used its size to obtain better terms on transportation and to undercut smaller rivals, softening them for purchase or forcing them out of business, the U.S. Supreme Court ordered that the company be dissolved on the grounds that it violated the Sherman Antitrust Act of 1890.

Khan (2017) argues that, since the 1970s and 1980s, antitrust cases have been looked at from the short-term interests of consumers, not from producers' interest or the long-term health of the market as a whole. Thus, antitrust doctrines view low consumer prices alone to be evidence of sound competition. Many of these services such as searching on Google and connecting with friends and acquaintances on Facebook are provided almost free or at subsidized prices to consumers. While Amazon decimated the fortunes of the publishing industry, it popularized e-book availability at $9.99 per book.[9] Because regulators have been unable to establish harm to end customers, they have found it difficult to force antitrust cases against the technology giants. For this argument, customers are defined at the individual level, not as the small businesses that advertise or sell through these platforms.

Furthermore, industry commentators often suggest that the dominant digital giants of today will eventually lose market share to upstarts or new entrants as seen with Nokia or Blackberry (Bourne 2019; McNish and Silcoff 2015). Among digital companies, the poster child examples for

[9] See https://mashable.com/2014/07/30/amazon-has-killed-publishers-they-just-dont-know-it-yet/.

this argument also include Yahoo! and Netscape that once held the world's leading positions in website visits and search engine usage but eventually lost their dominance when technologically superior rivals came along. The defenders of the status quo argue that today's market dominance is not an indicator of anticompetitive behavior or long-term dominance. For example, in 2007, Nokia controlled almost 50% of the world's smartphone market. By 2013, its share had fallen to less than 5%. Advocates argue that the digital giants spend billions on R&D every year in fear of becoming the next Nokia. Incidentally, those billions depress accounting rates of return that previous research has relied on to address the question of whether technology giants earn abnormal profits. Instead, we rely on an alternative method of computing abnormal profits advocated by Fisher and McGowan (1983) and Baber and Kang (1996).

3. Comparing ARR and IRR

Fisher and McGowan (1983) define the economic rate of return on an investment as the discount rate that equates the present value of its expected net revenue stream to its initial outlay. They go on to highlight that ARR, which is basically ROA, fails to capture economic return on an investment for four reasons.[10] First, financial reporting depreciation schedules, especially the straight-line method most commonly inherent in ARR, rarely reflect the stream of benefits emanating from an investment. Second, ARRs are reported for the firm as a whole and, by definition, would be an average of the ARRs for individual investments made in the past.[11] The weights in that average would consist of the book values of those different investments, which in

[10] ARR is calculated by adding interest expense and minority interest in income to income before extraordinary items, the resultant sum of which is scaled by beginning-of-year total assets. This measurement is consistent with Baber and Kang (1996) in that the pre-tax interest expense is added back. Adding back post-tax interest expense lowers the ARRs, which, as we show later, is already lower than IRRs for most tech firms.

[11] Some researchers believe that Bureau of Economic Analysis (BEA) adjusts for intangibles in estimation of national income. While we acknowledge that BEA includes intangible output, such as Microsoft Windows or musical recordings, in its new national income calculation, we could not find any evidence that BEA performs micro-level adjustments at the firm level, such as for R&D and SG&A expenses, for example, in its national income calculation.

turn depend on the depreciation schedule adopted and, particularly, on the amount and timing of such investments. Third, unless a few very restrictive assumptions hold (the proportion of investments with a given time shape of benefits from such investments remains fixed every year and the firm simply grows exponentially, increasing investments in each and every type of asset by the same proportion for every year), ARR to the firm as a whole would not be constant and would not equal the economic rate of return. Fourth, only when the ARR equals the growth rate of investment would the economic rate of return be the ARR.

Fisher and McGowan (1983) attracted much commentary (Long and Ravenscraft 1984; Martin 1984; Van Breda 1984; Horowitz 1984). Long and Ravenscraft (1984) argue that ARRs and economic rates of return are correlated in the cross section and, hence, ARRs remain relevant to the conversation about abnormal profits of firms or industries, especially because they are based on widely used accounting numbers. We do not claim that ARRs are totally irrelevant. We merely argue that IRRs can supplement information from ARRs, at least in the instances in which ARRs suffer from known limitations. Nevertheless, some of these papers remain uncomfortable with IRR because it is based on several assumptions about the length and time shape of benefits generated by investments, the growth rate of investments (as elaborated in Section 3.1), and the depreciation methods used for financial reporting purposes. Yet, the same criticisms apply to ARRs, perhaps to an even greater extent. ARRs rely on several assumptions including the revenue recognition principle, conservative accounting, and dependence on straight-line depreciation. In particular, Salamon (1985) shows that differences between ARRs and economic rates of return depend on the exact depreciation methods used by the firms under study (accelerated versus straight line) and the size of firms as both these factors are correlated with the depreciation methods used. In our sample (discussed in Section 3), there is little cross-sectional variation in method of depreciation as a majority of firms rely on straight-line depreciation for financial reporting.

We now turn to a detailed discussion of the empirical estimation of the economic rate of return. We rely on the Baber and Kang (1996) version of the estimation as that research was produced in response to an explicit request by the Office of Technology Assessment: to compare the IRR of a sample of firms in the pharmaceutical industry with IRRs of non-pharmaceutical companies. The method, pioneered by Ijiri (1978, 1979, 1980) and Salamon (1982, 1985), calculates a "cash recovery rate" from accounting data, which can then be combined with assumptions about the time profile of cash flows to infer an IRR for the industry.

3.1 Details associated with IRR computation

The calculation of IRR potentially mitigates some of the limitations associated with ARR, as pointed out by Fisher and McGowan (1983). IRR is based on cash recovery rate each year, following Ijiri (1978, 1979, 1980). To compute cash payouts, we start with after-tax operating income and add back depreciation and amortization and the annual R&D.[12] Decreases in noncash working capital and proceeds from the sale of invested capital, if any, are also added back to incorporate cash recoveries from any sale of past investment in the numerator. Along with these computations made in prior literature, we add back 50% of SG&A (excluding R&D). The running totals of last five years' R&D and 50% of SG&A (excluding R&D) for the last three years are added to invested capital. Invested capital is based on gross property, plant, and equipment, not depreciated values, and includes capitalized R&D and SG&A.

[12] Baber and Kang (1996) aggregates data at the industry level to calculate industry IRR. We conduct a finer analysis at the firm level, especially because we investigate tech giants' performance individually. We then calculate industry-level performance as weighted or simple average. In addition, Baber and Kang (1996) presents a range of estimates. We provide a point estimate for our base case and the other estimates for alternative assumptions.

In effect, the numerator is a close approximation of cash generated from operations, treating outlays on R&D, 50% of SG&A, PP&E, net working capital, and financial assets as investments. The denominator carries all investments (PP&E, working capital, acquisitions, financial assets, and intangible expenditures) at their initial values until the time they are sold or retired. Neither the numerator nor the denominator is affected by revenue recognition and depreciation schedule. For growing companies, R&D and SG&A capitalizations increase the numerator representing cash recoveries as well as the denominator of invested capital.

We overcome the single-period nature of ARR by making assumptions about the payback profile, that is, how long it takes to pay back an investment and what percentage of that payback occurs in each future period, following Salamon (1982). For example, if any investment pays back a total of $12 with a Q1 profile (Fisher and McGowan 1983), spread over *N* years, then assuming an *N* of 9 implies a pay back of $0, $0, $0, $1, $2, $3, $3, $2, and $1 in the first, second, third, fourth, fifth, sixth, seventh, eighth, and ninth year, respectively, after the initial investment. This payback assumes a gestation period of three years, a rise in recoveries over the next three years, followed by a decline.

If those paybacks follow the Q1 profile and occur with a 20% IRR, then following a $1 investment, the cash flows over the next nine years would be $0, $0, $0, $0.26, $0.53, $0.79, $0.79, $0.53, and $0.26 dollars, respectively, for a total of $3.17. The total inflows are almost three times larger than the initial investment, yet the IRR is only 20%. Also noteworthy is the fact that ARR does not account for the discount factor for cash flows that occur in different time periods.

Further assume that, each year, a company makes a net new investment (new outlay minus sale of old assets) that is 5% larger than the last year. Because the payback occurs over nine years, the undepreciated value of invested capital is a running total of the last nine years' investments.

For example, net new investments of \$100, \$105, \$110, \$116, \$122, \$128, \$134, \$141, \$148, and \$155, growing at a 5% rate, would lead to an invested capital of \$1,258 at the end of nine years. The cash recovery in the tenth year based on Q1 profile would be the sum of nine recoveries, 0% of the ninth year investment (that is, of $t-1$ investment), 0% of the eighth year investment (that is, of $t-2$ investment), 0% of the seventh year investment (that is, of $t-3$ investment), 26% of the sixth year investment (that is, of $t-4$ investment), 53% of the fifth year investment (that is, of $t-5$ investment), 79% of the fourth year investment (that is, of $t-6$ investment), 79% of the third year investment (that is, of $t-7$ investment), 53% of the second year investment (that is, of $t-8$ investment), and 26% of the first year investment (that is, of $t-9$ investment), amounting to \$377. The cash recovery rate (CRR) for the tenth year would then be \$377 divided by total invested capital at the beginning of tenth year (\$1,258), which is 30%. Note that CRR also includes return of principal and, therefore, it differs from IRR.

For a given payback profile (Q1 in this case), growth rate in invested capital, and IRR, there will be a unique CRR. Conversely, for a given payback profile, growth rate in invested capital, and CRR, there exists a unique IRR. We first calculate CRRs and then derive the implied IRR as the real root of R that solves equation (1) (Baber and Kang 1996), with R being 1 plus implied IRR.[13]

$$CRR_t = \left[\frac{Q_1(k)}{R^1} + \frac{Q_2(k)}{R^2} + \frac{Q_3(k)}{R^3} + \frac{Q_4(k)}{R^4} + \frac{Q_5(k)}{R^5} + \frac{Q_6(k)}{R^6} + \frac{Q_7(k)}{R^7} + \frac{Q_8(k)}{R^8} + \frac{Q_9(k)}{R^9} + \frac{Q_{10}(k)}{R^{10}}\right]^{-1} \times$$
$$\left[\frac{Q_1(k)\times G^9+Q_2(k)\times G^8+Q_3(k)\times G^7+Q_4(k)\times G^6+Q_5(k)\times G^5+Q_6(k)\times G^4+Q_7(k)\times G^3+Q_8(k)\times G^2+Q_9(k)\times G^1+Q_{10}(k)\times G^0}{G^9+G^8+G^7+G^6+G^5+G^4+G^3+G^2+G^1+G^0}\right] \quad (1)$$

[13] Baber and Kang (1996) conclude that relaxing the assumption of constant investment growth rate and allowing year-to-year fluctuations in growth do not alter their inferences. $Q10$ is zero, so it does not affect the formula in our main tests.

CRR for each year is calculated by dividing cash recovered (*CF*) by total investments at the end of prior year (*INVESTMENT*), and constant investment growth rate *G* is calculated as the geometric mean of year-over-year growth in *INVESTMENT*.[14]

We illustrate this methodology using accounting data from Compustat for Amazon, with all numbers used in the calculation inflation-adjusted to year 2000 value. For fiscal year 2018, Amazon's *CF* works out to $57,144 million. *INVESTMENT* at the beginning of the year is $184,321 million, which leads to *CRR* of 0.310.[15] The constant investment growth rate, *G*, is calculated as the geometric mean of year-over-year growth in *INVESTMENT* over 1997–2019 with available data (for Amazon, 53.7% or 1.537). Setting *G* equal to 1.537 and *CRR* equal to 0.310 in equation (1), we obtain a solution of 0.7169, which is equal to $1 / R$. Because $R = 1 + \text{IRR}$, the implied IRR is thus 39.5%.

We acknowledge that the IRR estimates are sensitive to assumptions about payback periods (e.g., Salamon 1982, 1985; Lee and Stark 1987; Gordon and Hamer 1988; Griner and Stark 1988). We conduct additional tests assuming a payback over four years, instead of nine years, and capitalizing 50% of R&D and 25% of SG&A, instead of 100% of R&D and 50% of SG&A. As discussed in Section 6, we find that our IRR calculations are largely robust to reducing the portion of investment capitalized. However, IRR calculations are sensitive to assumptions about the length of the payback period. Reducing the payback period to four years reduces IRRs for most companies

[14] *CF* is calculated as operating income before depreciation (OIBDP) + R&D expense (XRD) + 50% of SG&A expense (XSGA) excluding R&D – income tax (TXT) + deferred income tax (TXDC) + decrease in noncash working capital (current assets – cash & short-term investments – current liabilities, or ACT – CHE − LCT) + proceeds from the sale of property (SPPE) + proceeds from the sale of investments (SIV). *INVESTMENT* is measured as total assets (AT) + accumulated depreciation (PPEGT − PPENT) + capitalized R&D expenses + capitalized SG&A expenses (50% excluding R&D).

[15] The *INVESTMENT* number is a combination of internal investments and acquisitions. The IRR method is robust enough to handle potentially different payoffs from these two types of investments. Assume that internal investments have a payoff for four years and that acquisitions pay off in seven years. The IRR model addresses both types of investments as cash recoveries from either investment occur within our assumed nine-year payback period. We also include robustness tests to accommodate other payoff profiles (see Table 10).

to negative numbers, unlike ARRs that are positive at mean and median levels. If ARRs are valid at least for low-tech and stable-tech companies, then the four-year payback period for IRR (which is entirely inconsistent with ARR) may not be a reasonable assumption. In comparison with our nine-year payback period assumption, Baber and King (1996) stipulate a payback period of 20 years, because pharmaceutical patents are protected for that time period.

3.2 Calculation of weighted-average cost of capital (WACC)

To put digital giants' computed IRR into perspective, we compare it with their cost of capital. We calculate firm-year weighted-average cost of capital using equation (2):

$$WACC = [R_e \times (1 - Debt\ Ratio)] + [R_d \times (1 - ETR) \times Debt\ Ratio], \qquad (2)$$

where R_e is cost of equity and R_d is cost of debt. Effective tax rate (*ETR*) and *Debt Ratio* are calculated using Compustat data.[16] Cost of equity is the risk-free rate plus equity risk premium. We obtain the monthly risk-free rate (i.e., the time series data on ten-year Treasury constant maturity bond rate) from Federal Reserve Economic Data (FRED) and average across a firm's fiscal year to obtain yearly values.[17] Risk premium is calculated as beta from the market model multiplied by historical implied equity risk premium.[18] Beta from the market model is extracted from the Beta Suite by WRDS (Wharton Research Data Services) using daily stock returns with 252 days in the estimation window and a minimum of 126 days, and it is recalculated on a daily basis. The daily beta values are then averaged across a firm's fiscal year to obtain the value for the year.

[16] Effective tax rate (*ETR*) is calculated as income tax expense (TXT) divided by pre-tax book income (PI) before special items (SPI), winsorized to 0 and 1. If *ETR* is missing, we use a median *ETR* value of 35%. *Debt Ratio* is calculated as total debt (DLTT + DLC) divided by the sum of total debt and market value of equity (PRCC_F × CSHO).

[17] Access Federal Reserve Economic Data at https://fred.stlouisfed.org/.

[18] Implied risk premium is the variable *Impl_FCFE* from Aswath Damodaran's website: http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/histimpl.html.

Cost of debt is the risk-free rate plus the credit spread. We obtain the monthly time series data on Moody's seasoned Aaa and Baa corporate bond yield relative to yield on ten-year Treasury constant maturity bond (i.e., credit spread) from FRED and calculate average yearly values. We then interpolate and extrapolate the credit spread for firms with credit ratings other than Aaa and Baa based on historical average spreads for each credit rating code.[19]

3.3 Tobin's Q

Tobin's Q is calculated by dividing market value of the firm by the replacement cost of its assets. Market value of the firm is calculated by adding the excess of market value of equity above its book value to the book value of assets. Replacement cost of assets is estimated from the book value of assets.[20]

4. Sample Selection and Descriptive Statistics

4.1 Sample

Our sample period spans 40 years between 1980 and 2019 and includes firm-years covered by Compustat and CRSP with $100 million in inflation-adjusted assets (adjusted to year 2000 value).[21] This filter limits the sample to economically substantial firms and minimizes the impact of less important firms with occasional outsized performance (Dichev and Tang 2009).

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[19] We calculate historical average spreads for each credit rating code based on data collected from bondsonline.com between 2008 and 2018. We then use Standard & Poor's domestic long-term issuer credit rating (SPLTICRM) from Compustat in our interpolation and extrapolation. When credit ratings are not available, we use "synthetic" ratings inferred from interest coverage ratio based on data provided on Aswath Damodaran's website: http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ratings.htm. Interest coverage ratio is calculated as earnings before interest and taxes (the first non-missing value from EBIT, OIADP, or SALE minus the sum of COGS, XSGA, and DP) divided by interest expense (XINT).

[20] Market value of the firm is calculated as market value of equity at fiscal year-end (PRCC_F × CSHO) + book value of assets (AT) – book value of equity, where book value of equity is calculated as shareholders' equity (SEQ) + deferred taxes (TXDB) + investment tax credit (ITCB) – preferred stock redemption value (PSTKRV). If PSTKRV is missing, preferred stock liquidating value (PSTKL) is used. If both PSTKRV and PSTKL are missing, then carrying value of preferred stock (PSTK) is used. Replacement cost of assets is estimated from the book value of assets. Tobin's Q is calculated for firms with positive shareholders' equity (SEQ).

[21] We obtain monthly Consumer Price Index (CPI) data for all urban consumers from the U.S. Bureau of Labor Statistics for inflation adjustment.

Table 1 presents our key sample selection steps. We start with 372,765 firm-year observations covered in the Compustat North America Fundamentals Annual database during 1980–2019 and remove 113,571 observations related to firms in the utilities, financials, and real estate sectors (firms with two-digit GICS code 40, 55, and 60) and firms with missing GICS codes. We then remove 83,337 firm-years without CRSP coverage or firm-years whose fiscal years end before the first date for which stock price data are on CRSP. Next, we remove 75,086 observations with inflation-adjusted assets less than $100 million, resulting in 100,771 observations before we calculate key variables used in our analyses. From this preliminary sample, we drop 1,005 observations without sufficient data to calculate cash recovery rate or accounting rate of return, 9,543 observations from firms with less than six years of data, and 2,636 observations with missing beginning-of-the-year market value of equity. These data requirements result in 87,587 firm-year observations for 6,570 unique firms in our main analyses. Sample sizes used in other analyses vary due to additional data filters.

[Insert Table 1 near here]

After applying the sample filters, we classify firms as low-, stable-, and high-technology firms based on the first six digits of their GICS codes using the definitions outlined in Mizik and Jacobson (2013), Chandler (1994), and Chan et al. (1990).[22] Low-tech firms represent the food, beverage, retail, hospitality, and consumer durables industries. Stable-tech firms operate primarily in industries related to transportation, automobiles, chemicals, energy, equipment, and machinery. We subdivide high-technology firms into the health-high-tech sector (health care equipment and

[22] We use GICS because GICS is popular among financial practitioners and it provides a significantly better technique for identifying industry peers than other classification schemes including Standard Industrial Classifications (SIC), North American Industry Classification System (NAICS), and Fama and French (1997) algorithm (Bhojraj, Lee, and Oler 2003). See Appendix A for details on the classification. We exclude financials, utilities, and real estate sectors because of their unique regulatory reporting environments.

services, pharmaceuticals, biotechnology and life sciences) and the digital-tech sector (information technology and communication services). Recent allegations of anticompetitive practices by regulators primarily apply to the digital-tech sector.

Panel A of Table 2 shows the number of firms in low-, stable-, and high-tech industries with inflation-adjusted total assets exceeding $100 million during our sample period. The number of digital-high-tech firms increased significantly during the 1990s, coinciding with the dotcom boom. We found 364 digital-tech firms in 1990. That number increases to 712 in 1999, grows to 804 in 2000, and peaks at 829 in 2001. The total number of firms in our sample is the highest at 2,749 in 2000. As documented before, several public firms have delisted, been acquired, or gone private since 2001.[23]

[Insert Table 2 near here]

Panel B of Table 2 shows that firm size, measured as year 2000-indexed inflation-adjusted assets, at the 75th percentile, has increased significantly.[24] The period after the financial crisis has witnessed at least a doubling of asset size in all tech sectors. At the lowest end of the range, the 75th percentile of asset size for low-tech firms has increased from $2.406 billion in 2009 to $4.047 billion in 2019. At the highest end of the range is the digital-tech sector in which the 75th percentile of asset size has increased from $2.46 billion in 2009 to $6.022 billion in 2019.

4.2 Descriptive statistics

Table 3 presents descriptive statistics of various variables used in our study for our sample firms. The upper half of the table contains the computed variables, and the lower half presents the numbers reported in financial statements. The computed *CF*, the numerator for *CRR*, is

[23] See, e.g., https://www.bloomberg.com/opinion/articles/2018-04-09/where-have-all-the-u-s-public-companies-gone.
[24] Median firm size shows a similar pattern. This is consistent with prior studies. See, e.g., https://hbr.org/2019/11/midsize-companies-are-growing-but-struggling-to-earn-profits.

significantly larger than operating income before depreciation (mean of $984 million versus $549 million and median of $175 million versus $85 million). This is because of the adjustments we make in the numerator, such as adding back a portion of intangible expenses and the liquidation of working capital and investments, if any. Because we include capitalized intangibles in the denominator and consider only the undepreciated values of PP&E, the mean ($6,363 million versus $4,081million) and median ($1,069 million versus $676 million) of *Investment* is much larger than total assets. This observation is supported by the fact that undepreciated value of PP&E is much higher than the depreciated values (mean $2,493 million versus $1,348 million). The mean and median *CRR*s are 0.193 and 0.171, respectively. The mean geometric growth rate of *Investment* is 10.8%. Accordingly, the average *IRR* is calculated at 0.117 (mean) and 0.108 (median), significantly higher than *ARR* of 0.064 (mean) and 0.071 (median).

[Insert Table 3 near here]

5. Empirical Results

We compute ARR and IRRs over time for different industry sectors. We perform the same analysis for tech giants.

5.1 Sector-wise profitability: ARR

We compute ARRs and IRRs for every firm in the sample over the period 1980–2019 and present summary statistics for the cross-sectional distribution of these return numbers, sorted by sector, in Panel A of Table 4. Predictably, the cross-sectional means of ARRs are lower for sectors that spend more on R&D, as U.S. GAAP requires mandatory expensing of R&D to report net income, the number underlying ARR. For instance, the mean ARR is 7.7% for the low-tech sector contrasted with 4.7% for the health-tech sector and 5.0% for the digital-tech sector. The cross-sectional means of ARRs reported in Table 3, by definition, imply equal weights on firms within a sector. The means also mask substantial time series variation across time. To enable inferences about the sector as a whole, we calculate the weighted-average ARR (weighted by beginning-of-the-year market value of equity) for each sector in each year and present the findings in Panels A and B of Table 5. Using weighted-average values allows us to incorporate the economic significance of each firm to its respective sector in our evaluation of overall sector performance.

[Insert Table 4 and Table 5 near here]

The time series trends of ARRs can be found in Figure 1 and Panel A of Table 5.[25] To appreciate the data better, consider the sector-wise ARR data presented by decades (1980–1989, 1990–1999, 2000–2009, and 2010–2019) in Panel B of Table 5. The sector-level ARR for the health-tech sector is the highest at 18.4% in the 2000–2009 decade. Low-tech ARRs dominate stable-tech ARRs for all the four decades presented and maintain an average and stable IRR between 11.2% and 12.7% in all four decades of our study period. Notably, the digital-high-tech sector does not dominate in any ten-year period, even in the last window spanning 2010–2019. ARRs for the digital-tech sector took a plunge during the dotcom bust, turning negative, and are not significantly different from zero in 2001 and 2002.[26]

[Insert Figure 1 near here]

5.2 Sector-wise profitability: IRR

Panel A of Table 4 reports cross-sectional means of IRRs for the four sectors investigated. Because IRR treats R&D and 50% of SG&A as an investment, as opposed to an expense, the numerator of the cash flows underlying IRR is higher for technology firms. However, the

[25] Market value of equity is calculated as stock price at the end of the fiscal year (PRCC_F) times common shares outstanding (CSHO), all adjusted to year 2000 values. All values are winsorized at the 1st and 99th percentile for the entire sample before calculating the average values.
[26] The plunge during the dotcom bust is not driven by outliers, as the median ARRs show a similar picture (untabulated).

denominator, which can be thought of as the asset base, implicitly includes such investment and hence sets a higher bar in terms of reporting payback rates. On top of that, the denominator in IRR, unlike ARR, incorporates the undepreciated value of assets.

The mean IRRs for the health care sector at 16.8% and for the digital-tech sector at 14.9% are noticeably higher than their ARRs partly because of their great reliance on R&D. The Spearman correlation between ARRs and IRRs are 48.7% and 51.2% for the low- and the stable-tech sector, respectively. They are lower at 32% and 35%, respectively, for the health-tech and the digital-tech sector. Nevertheless, these correlations are nowhere close to 95% or higher correlations among different IRRs calculated using alternative assumptions of intangibles capitalization and payback profiles, discussed in Section 6.

Figure 2, Panel A, and the associated table (Panel A of Table 5) presents the weighted-average IRR (weighted by beginning-of-the-year market value of equity) for each sector in each year. Profitability, as measured by IRRs, shows a different rank order and time trend relative to those measured by ARRs. The data for the low-tech and stable-tech industries contradict the perception that ARRs are always lower than IRRs. For instance, in the 2010–2019 window, as seen in Panel B of Table 5, the ARR for the low-tech sector at 11.2% is not statistically different from the IRR for that sector. In the stable-tech sector, for the same time period, ARR of 7.3% is higher than the IRR of 5.3%.

[Insert Figure 2 near here]

These trends reverse for the health and digital sectors. For the period 2010–2019, the health sector–wide IRR is 16.4% relative to an ARR of 8.9%. For the digital-tech sector, the IRR is 17.4% relative to a 9.9% ARR. Most interesting, perhaps, is that the IRR for the digital-tech sector at 17.4% is almost the same as the 16.4% for health-tech. For the digital-tech sector, IRRs start exceeding ARRs and the difference opens up in the 21st century, amounting to 6%–7% on average. Hence, a researcher and policy maker would reach different conclusions with IRRs than with ARRs, on the performance for high-technology firms, at least in the 21st century.

We conduct another test to assess the performance of the digital-high-tech sector. We identify the top 100 firms by IRR each year and examine which industry sector contributes those firms. We then calculate the averages by decade: 1980–1989, 1990–1999, 2000–2009, and 2010–2019. Figure 3 and Panel B of Table 4 show that the contribution of low-tech and health-high-tech to top IRR performers has declined while that of digital-high-tech has increased. After the 2008 crisis, digital-high-tech has the largest share among the top IRR performers. This trend cannot be attributable solely to the growing number of digital-tech firms in our sample because that number increased in the 1990s with the listing of numerous dotcom firms. However, the share of digital-tech firms among the top 100 IRRs declined during the same period.

[Insert Figure 3 near here]

5.3 IRRs versus ARRs for digital giants

The ARRs of the tech giants are presented in Panel B of Figure 1 and Panel A of Table 6. Microsoft reports the highest ARR during our study period, while exhibiting a declining trend in the 21st century. During most of the 21st century, Apple shows an ARR of about or exceeding 20%, which, arguably, could explain its inclusion in the Berkshire Heathway's portfolio that typically focuses on value stocks. Facebook, a relative newcomer, reports an increasing ARR. Amazon is the least profitable, consistent with its willingness to assume losses in at least some parts of its business to gain market share. Remarkably, the ARRs for Alphabet has fallen from its initial highs between 2005 and 2010 to a more conventional range of between 7% and 15% during the years 2016–2019.

[Insert Table 6 near here]

Panel C of Table 6 shows that WACC has fallen over time but exceeded 10% in the first half of our study period. In that case, tech giants, particularly Amazon, earned negative net returns in several years (ARR was less than cost of capital, interpretable as destruction of economic value), which seems inconsistent with the euphoria surrounding those companies in the 1990s. Because the WACCs are consistent with intuition, averaging 10.3% in the 1990s, the error most likely lies in ARR calculation.

The IRR data for the digital giants, shown in Panel B of Figure 2 and Panel B of Table 6, present an entirely different picture. We first report the most surprising results to illustrate this contrast. Amazon's ARRs for the years 1998, 1999, 2000, and 2001 are -65%, -95%, -50%, and -19%, respectively. IRRs for the same years not only flip sign but become as high as 63%, 49%, 30%, and 26%, respectively. IRRs exceed 30% since 2002, a return not apparent in Amazon's ARRs. For 2010–2019, Amazon reports ARRs of 8%, 4%, 0%, 1%, 0%, 2%, 4%, 5%, 9%, and 8%. IRRs for the same period are 51%, 53%, 46%, 42%, 43%, 41%, 41%, 41%, 39%, and 39%. The IRRs and ARRs routinely differ by 30% or even 40% in certain years. Barring Alphabet, all digital giants show IRRs in excess of 30% since the 2008 financial crisis, even exceeding 50% in certain years.

These results are based on invested capital, which is un-depreciated property, plant, and equipment and a large amount of inventory carried by Amazon. The IRR results are further enhanced by the capitalization of R&D, 50% of SG&A, and purchased intangible investments. IRRs of such large magnitudes conditioned on massive investments could be indicative of supernormal profits. Panel C of Table 6 shows that WACC of these firms is either constant or has declined over the past two decades. In the most recent decade, WACC is less than 10% for all tech giants. As a result, the difference between IRR and WACC for these tech giants has dramatically widened in the 21st century.

5.4 Additional evidence with Tobin's Q

Many prior studies (e.g., Gutiérrez and Philippon 2017) consider Tobin's Q as a measure of abnormal profits. Panel A of Table 7 shows that Tobin's Q is much larger for tech firms, exceeding 2.0 for most years, than for low- or stable-tech sector. For tech giants, the average Tobin's Q exceeds 3.5 in all four decades. However, it has declined over time. Panels B–E present results of a regression of Tobin's Q on IRR and ARR, by sector and by decade. The results suggest that IRR is significant for all four clusters in all four decades, indicating that IRR carries value-relevant information orthogonal to ARR. For the low- and stable-tech sector, the coefficient on ARRs is higher than that on IRR, at least in the 21st century. In contrast, the coefficient on IRR is significantly higher than that for ARRs for high-tech firms (both health-tech and digital-tech sectors). For health-tech, the coefficient on ARR is either insignificant or negative. These results suggest that, for high-tech firms, IRR carries more relevant information in explaining cross-sectional variation in Tobin's Q than does ARR. To the extent Tobin's Q proxies for abnormal rents (McFarland 1987), results indicate that IRR is a more valid measure of abnormal rents for tech firms than ARR, at least in the 21st century.

[Insert Table 7 near here]

5.5 Antitrust cases as a reference point

High IRRs of the digital-tech sector and tech giants per se do not establish that these firms indulge in anticompetitive practice to earn excessive profits. As a benchmark, we estimate IRRs of firms investigated by the DOJ Antitrust Division in the five years (and inclusive of the first year) preceding investigation and calculate the average IRR during those years.[27] For multiple investigations for the same company or investigations over multiple years, we use data for the five years preceding (and inclusive of the first year) the first case investigated. We retain 55 firms (including three tech giants: Apple, Microsoft, and Alphabet) with available data (excluding tech giants improves the reported results).[28] Appendix C has a list of these companies, and Table 8 shows that the average IRR of the investigated firms is 13%. In comparison, digital giants now report IRRs in excess of 30% or even 50% in the post-2008 period. We do not claim that high IRRs alone should be the basis for ascertaining anticompetitive behavior. Yet, these results show that digital giants earn far higher profits than the companies that are typically investigated by the DOJ.

[Insert Table 8 near here]

6. Additional Analyses

In this section, we examine the factors that could cause difference between IRR and ARR and calculate IRRs with alternative assumptions.

6.1 Determinants of difference between IRR and ARR

We estimate the following regression where the difference between IRR and ARR is the dependent variable and various firm-level determinants are independent variables.

[27] We collect antitrust cases during our study period using two sources on DOJ's website. First, we identify firms discussed in annual review articles published on https://www.justice.gov/atr/public-documents/rio-annual-review-articles. These review articles emphasize cases that raise interesting and complex economic issues. Second, we use a filter by topic and select "Antitrust" on https://www.justice.gov/atr/antitrust-case-filings-alpha. We match firm names to Compustat companies and identify case filing dates when available.

[28] An antitrust complaint was filed in 2010 against Apple and a few other tech companies for their bilateral no cold call agreements that eliminated competition to attract high-tech employees. The tech companies entered into a settlement with the DOJ. The DOJ filed a case against Microsoft in 1998 for anticompetitive practices (e.g., bundling of software programs into its operating system) to protect its monopoly. After several years of legal proceedings, the DOJ sought a lesser antitrust penalty and a settlement was entered in 2001. In 2008, the DOJ informed Google and Yahoo! Inc. that it would file an antitrust case against them for an advertising agreement that would result in higher prices and weaken competition by Yahoo! against Google. The companies abandoned their agreement as a result.

$$
\begin{aligned}
IRR\_ARR\_Diff_{i,t} = {} & \beta_0 + \beta_1 \times INVENTORY_{i,t} + \beta_2 \times PPE_{i,t} + \beta_3 \times INTANGIBLES\_BS_{i,t} \\
& + \beta_4 \times RD\_INTENSITY_{i,t} + \beta_5 \times SGA\_INTENSITY_{i,t} + \beta_6 \times LOSS_{i,t} \\
& + \beta_7 \times RD\_GROWTH_{i,t} + \beta_8 \times SGA\_GROWTH_{i,t} + \beta_9 \times AGE_{i,t} \\
& + \beta_{10} \times MARKET\ SHARE_{i,t} + \varepsilon_{i,t} \qquad (3)
\end{aligned}
$$

All variables are defined in Appendix B. The regression includes year fixed effects. Regression results by sector and decade are presented in Panels A–D of Table 9. Across industry sectors, in most regressions, R&D and SG&A intensities load significantly, likely because R&D and a part of SG&A expenses are added back to the numerator in calculations of IRRs. This pattern is consistent in the most recent decade, 2000–2009. Two other variables that load significantly across sectors are *Loss* (positive) and *Age* (negative). The negative coefficient for *Age* likely indicates that intangible investments of young firms have not started paying off yet, creating a large mismatch between the investments and current profits. Thus, the single-period ARR under-represents their underlying profitability. In contrast, mature firms are likely in steady state, and their current profits are reasonably matched to their overall investments. The explanation for *Loss* is not straightforward. One conjecture is that many loss firms are firms that either report a one-time unusually large loss or are firms that focus on R&D activities but have little sales (Masako and Ye 2007). Thus, ARRs may be noisy signals of underlying profitability for firms that report losses.

[Insert Table 9 near here]

For the health-tech and digital-tech sectors, which have the largest differences between ARR and IRR, the adjusted R-squareds for the most recent decade are about 40% and 50%, respectively, indicating that the variables included in the regression have reasonable explanatory power. Other than factors discussed above, the coefficient on *PPE* is negative and significant. The interpretation is that the IRR-ARR difference is lower for high-tech firms relative to the others if the high-tech firms operate with a larger fixed asset base.

6.2 Sensitivity tests on IRR calculation

We make three key assumptions in our calculations of IRR: payback period (nine years), percentage of paybacks during the payback periods (Q1 profile: $12 distributed over the next nine years in the proportions of $0, $0, $0, $1, $2, $3, $3, $2, and $1), and the extent of intangibles to be capitalized (100% of R&D expenses and 50% of annual SG&A). We perform sensitivity tests by changing these assumptions one at a time. We first assume that payback period is four years, instead of nine years. Table 10 shows that both the mean and the median IRRs turn negative for a large percentage of firms (mean is -0.032 and median is -0.046). These values are largely inconsistent with reported ARRs, which are positive on average (mean is 0.064 and median is 0.071). Unless one believes that ARRs are entirely wrong and are overestimated, a short payback period would not be a valid assumption. We conduct an additional test using 20 years as the payback period to accommodate the objection that health care firms have longer payoff periods (Baber and Kang 1996). This test leads to a severe reduction in sample size and increases the estimated IRRs by 1% to 2% on average for different clusters and periods (results not tabulated). Nevertheless, the Spearman correlation between base-case IRRs and the new IRRs remains at about 0.95, so the relative rankings remains largely unchanged.

[Insert Table 10 near here]

We next use the Q2 profile (Baber and King 1996) that assumes no gestation period compared with a three-year wait period for the Q1 profile. The differences between IRRs of the Q1 and Q2 profiles are not economically significant. The mean and median for the Q2 profile is higher by 0.5% and 0.4%, respectively, because of earlier payback. We then reduce the extent of intangibles capitalized (50% instead of 100% of R&D expenses and 25% instead of 50% of SG&A). This change reduces IRR by 2.7% and 2.8% at the mean and median level, respectively, suggesting that the extent of intangible capitalized affects IRR calculations. Hence, R&D levels should at least partly explain the difference between ARR and IRR, an issue confirmed in Table 9.

These findings open up the larger question of the level of intangibles that should ideally be capitalized. Several results presented in this paper show that the assumption of entire expensing is not valid unless stock market valuations are totally wrong. Panels A and C of Table 6 show that net returns (ARR above WACC) are negative for tech giants in many years, which seems inconsistent with their valuation in excess of $500 billion dollars in the same years. Panel B of Table 7 shows that Tobin's Q, a variant of market-to-book ratio, is more strongly associated with IRR than ARR. To the extent the differences between IRR and ARR arise because of the capitalization of intangibles, the market-based metrics weigh more in the favor of IRR than ARR.

Nevertheless, Panel B of Table 10 shows that neither of these variations for sensitivity tests changes the overall rankings of IRRs. The rank correlations among the three IRR measures are at least 95%. Recall, in comparison, that the correlation between ARR and IRR is much lower, ranging from 35% to 52% (Table 4, Panel A). IRRs calculated with the 50% of intangibles capitalized, as a base case, are correlated at 97.9% with the original IRRs. Therefore, conclusions about which type of firms make higher, if not abnormal, profits would remain largely unaltered if the researcher were to change assumptions about the extent of intangibles capitalized.

6.3 ROIC tests

We conduct another test using ROIC, which is calculated by modifying numerator and denominator in ARR calculation. We add back the after-tax impact of net investment in intangibles, previously deducted in the calculation of numerator. Net investment is obtained by subtracting depreciation of intangible stock (assuming three- and five-year lives for R&D and SG&A investment, respectively) from current R&D plus 50% of SG&A. In the denominator, we add capital stock of intangible investment but subtract cash holdings. Panel A of Figure 4 presents the sector-wise ROICs over time, and Panel B shows ROICs for the tech giants. It is noteworthy that ROICs are higher than ARRs for tech companies, so much so that the digital-tech cluster has become the best-performing sector in the economy after 2008. However, the magnitude of such ROICs is relatively modest ranging between 10% and 14%.

Ayyagari et al. (2020), using a highly unconventional measure of ROIC, find that the profitability of all tech giants, except Amazon, exceeds the 90th percentile performance of all firms.[29] Nevertheless, we view ROICs as a measure that falls in the continuum between ARR and IRR. ROIC continues to suffer from most of the limitations of ARR detailed in Section 3. Ayyagari et al. (2020) also calculate sales to cost-based "markups" as evidence of tech giants' competitive advantage. Similarly, Loecker et al. (2020) find that increased market power is associated with higher price markups. We do not conduct this test for two reasons. First, apart from the general concern associated with the measurement of markups (Basu 2019; Syverson 2019), we are not sure how to define markups for technology firms that sell services (e.g., Facebook or Google) or pharmaceutical products (the main cost of drugs is R&D or acquired R&D, not raw materials).

[29] Ayyagari et al. (2020) go a step further in increasing the numerator while reducing the denominator in their calculation of ROIC. Their return is based on pre-tax earnings, despite the common understanding that investors get paid from post-tax income. They add the capital stock of R&D but remove goodwill from invested capital. It is thus questionable why they include earnings from acquisitions but remove the bulk of acquired assets from invested capital. They depreciate R&D capital stock but do not amortize intangibles. They subtract current liabilities from invested capital presumably because that portion of working capital is funded by trade creditors and not investors. However, this assumption could have a significant impact for a company such as Amazon, which operates with negative working capital. Furthermore, they do not include numerous asset items that are part of the firm's asset base but are not included in PP&E and current assets, such as IPR&D, deferred tax assets, and other assets.

Second, even for firms that sell physical products, a markup is very difficult to estimate using publicly available data.[30]

[Insert Figure 4 near here]

6.4 Additional tests to address survival bias and under-reporting of stock option expenses

A limitation of the IRR method is that it requires long time series data. So, IRR estimates are affected to a greater extent by survival bias relative to ARRs. Survival bias can particularly distort average IRR for technology companies that make risky bets on new business ideas and innovative products. For example, out of 4,000 molecules at the laboratory stage for pharmaceutical firms, only one reaches commercial success. We observe the selected sample that succeeds with such lottery-like payoffs, not those that went bankrupt, got delisted, or were acquired. We conduct another test to partially address survivorship bias. We assume that cash flows in the delisting year and subsequent eight years is zero. For the companies that got acquired, we assume that cash flows in the delisting year is the purchase consideration paid by the acquirer as per the Securities Data Company (SDC) database. The subsequent eight years' cash flows are assumed to be zero. The recalculated average IRR declines for all industries, but more so for health-tech (by approximately 2%) and digital-tech (1.5%) (results not tabulated). Nevertheless, our overall conclusions and ranks of IRR remain unchanged.

Employee expenses are a major cost for technology companies, which are often paid via stock options, whose costs are recognized based on option-valuation methods estimated on the grant dates. Actual payoffs to employees, especially for surviving firms, typically far exceed the

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[30] Ayyagari et al. (2020) use two ratios: Revenues / COGS (cost of goods sold) and Revenues / Total Operating Expenses to measure price-cost markups. We believe that COGS is not defined for service firms and is not a meaningful concept for pharmaceutical firms. We are unclear how total operating expenses can be used to determine price-cost markups. Furthermore, it is not obvious why Ayyagari et al. (2020) add back R&D and SG&A but fail to subtract the associated depreciation related to R&D and SGA in calculating operating expenses.

recognized expenses. So, a technology firm's employee costs may be underestimated in the calculation of its cash flows (we subtract 50% of SG&A expenses in the calculation of cash recovered for *CRR*). We conduct another test by recalculating the SG&A expenses in the post–Statement of Financial Accounting Standards (SFAS) 123R period. We assume that the real cash flow cost of stock options is twice that of the expense reported by the company. Thus, we increase SG&A expenses by the recognized stock option expense, both in the calculation of numerator (decreases) and the capitalized amounts in denominator (increases). While IRR reduces, the reduction is not economically significant for any category of companies.

7. Conclusions

We address the limitations inherent in accounting measures of profitability (such as ROA and ROIC) by using an alternative method (that is, IRR) to inform the debate on economic profitability of technology firms in general and of the digital giants in particular. We provide stylized evidence that differs from the evidence drawn based on accounting returns. We find that the digital-tech cluster has become the best-performing sector in the economy and the performance gap of that cluster with respect to low-tech and stable-tech sectors is increasing. In addition, digital giants routinely earn IRRs exceeding 40%. Notably, this IRR is based on a large invested capital base that includes undepreciated values of PP&E and capitalized values of intangibles. The gap between their IRRs and cost of capital has also widened dramatically.

We must, however, caution that, as any yardstick of profitability including ARR and our estimation of IRRs is dependent on multiple assumptions, including the amounts of intangibles capitalized and the lengths of payback periods. Nevertheless, in contrast to ARR, we make fewer restrictive assumptions about the depreciation schedules and whether an investment's payoff occurs in the same period. More important, firms' ranks with respect to the IRRs are largely robust to assumptions about the amounts of intangibles capitalized and the lengths of payback periods. That is, firms that report highest IRRs under one set of assumptions would also report the highest IRRs under another set of assumptions. We hope our work provides an alternative perspective and furthers the debate about the economic profitability of the digital technology sector.

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Appendix A: Industry Classification

All firms are classified into one of four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their GICS codes. This Appendix presents industries in each sector.

Low-Technology	**Stable-Technology**	**Health-High-Technology**	**Digital-High-Technology**
Beverages	Aerospace & Defense	Biotechnology	Communications Equipment
Building Products	Air Freight & Logistics	Health Care Equipment &	Diversified Telecommunication
Commercial Services & Supplies	Airlines	Health Care Providers & Services	Electronic Equipment, Instruments &
Construction & Engineering	Auto Components	Health Care Technology	Entertainment
Construction Materials	Automobiles	Pharmaceuticals	Information Technology Services
Containers & Packaging	Chemicals	Life Sciences Tools & Services	Interactive Media & Services
Distributors	Electrical Equipment		Internet & Direct Marketing Retail
Diversified Consumer Services	Energy Equipment & Services		Internet Software & Services
Food & Staples Retailing	Industrial Conglomerates		Media
Food Products	Machinery		Office Electronics
Hotels, Restaurants & Leisure	Marine		Semiconductor Equipment & Products
Household Durables	Metals & Mining		Semiconductors & Semiconductor
Household Products	Oil, Gas & Consumable Fuels		Software
Leisure Products	Road & Rail		Technology Hardware, Storage &
Multiline Retail	Transportation Infrastructure		Wireless Telecommunication Services
Paper & Forest Products			
Personal Products			
Professional Services			
Specialty Retail			
Textiles, Apparel & Luxury Goods			
Tobacco			
Trading Companies & Distributors			

Appendix B: Variable Definition

Variable	Definition
Calculation of ARR and IRR	
IRR	Internal rate of return is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile and constant growth rate in investment. Under the profile used in our main analysis, a firm's total investments generate cash payouts within the next ten years with no payouts in the first three years followed by increasing payouts between year four and year six, and then decreasing payouts from year seven to year ten, with zero payout in year ten. All numbers used in the calculation are inflation-adjusted to year 2000. Section 3 describes the calculation in detail.
ARR	Accounting rate of return is calculated as income before extraordinary items (IB) + minority interest (MII) + interest expense (XINT), divided by beginning total assets (AT). ARR is set to missing if IB is missing. IB, MII, XINT, and AT are Compustat variables.
CRR	Cash recovery rate is calculated as cash recovered (CF) divided by beginning investments (INVESTMENT).
CF	Cash recovered is calculated as operating income before depreciation and income tax (OIBDP) + R&D expense (XRD) + 50% of SG&A (XSGA) excluding R&D − income tax (TXT) + deferred income taxes (TXDC) + decrease in noncash working capital + proceeds from the sale of invested capital. Noncash working capital is current assets (ACT) minus cash and short-term investment (CHE) minus current liabilities (LCT). Proceeds from the sale of invested capital is from sale of property (SPPE) and sale of investments (SIV). Cash recovered is set to missing if OIBDP is missing. Other variables used in this calculation are treated as zero if missing. OIBDP, XRD, XSGA, ACT, CHE, LCT, SPPE, and SIV are Compustat variables.
INVESTMENT	Invested capital is calculated as total assets (AT) + accumulated depreciation (PPEGT minus PPENT) + capitalized R&D expense from the past five years (XRD) + capitalized SG&A (XSGA) excluding R&D from the past three years. Invested capital is set to missing for firms with negative AT. Other variables used in this calculation are treated as zero if missing. AT, PPEGT, PPENT, XRD and XSGA are Compustat variables.
G_ANN	Annual growth rate in *INVESTMENT*, calculated as *INVESTMENT* at year t divided by *INVESTMENT* at year t - 1.
G	Constant geometric mean in annual investment growth rate, calculated from *G_ANN* over the sample period.

Appendix B continued

Variable	**Definition**
MVE	Market value of equity is calculated as fiscal year-end stock price (Compustat PRCC_F) × common shares outstanding (Compustat CSHO).
TOBIN'S Q	Tobin's Q is defined as market value of the firm over the replacement cost of its assets. Market value of the firm is calculated as market value of equity at fiscal year-end (PRCC_F × CSHO) + book value of assets (AT) – book value of equity, where book value of equity is calculated as shareholders' equity (SEQ) + deferred taxes (TXDB) + investment tax credit (ITCB) – preferred stock redemption value (PSTKRV). If PSTKRV is missing, preferred stock liquidating value (PSTKL) is used. If both PSTKRV and PSTKL are missing, then carrying value of preferred stock (PSTK) is used. Replacement cost of assets is estimated from the book value of assets. Tobin's Q is calculated for firms with positive shareholders' equity (SEQ). PRCC_F, CSHO, AT, SEQ, TXDB, ITCB, PSTKRV, PSTKL, and PSTK are Compustat variables.
WACC	Weighted-average cost of capital is calculated as $[R_e \times (1 - Debt\ Ratio)] + [R_d \times (1 - ETR) \times Debt\ Ratio]$. R_e is cost of equity calculated as the risk-free rate plus equity risk premium. R_d is cost of debt calculated as the risk-free rate plus the credit spread. R_e and R_d are calculated using data from Federal Reserve Economic Data and Aswath Damodaran's website. Effective tax rate (*ETR*) is calculated as income tax expense (TXT) divided by pre-tax book income (PI) before special items (SPI), winsorized to 0 and 1. If *ETR* is missing, we use median *ETR* value of 35%. *Debt Ratio* is calculated as total debt (DLTT + DLC) divided by the sum of total debt and market value of equity (PRCC_F × CSHO). TXT, PI, SPI, DLTT, DLC, PRCC_F, and CSHO are Compustat variables. Section 3 describes the calculation in detail.
INVENTORY	Inventory (Compustat INVT) divided by total assets (Compustat AT).
PPE	Property, plant, and equipment (Compustat PPENT) divided by total assets (Compustat AT).
INTANGIBLES_BS	Sum of intangible assets (INTAN) and goodwill (GDWL) divided by total assets (AT). INTAN, GDWL, and AT are Compustat variables.
RD_INTENSITY	R&D expense (Compustat XRD) divided by sales (Compustat SALE).
SGA_INTENSITY	SG&A expense (Compustat XSGA) divided by sales (Compustat SALE).
LOSS	Indicator variable that equals one if income before extraordinary items (Compustat IB) is less than zero.
RD_GROWTH	R&D expense (Compustat XRD) relative to assets (Compustat AT), divided by prior year's R&D expense relative to assets.

Appendix B continued

Variable	**Definition**
SGA_GROWTH	SG&A expense (Compustat XSGA) relative to assets (Compustat AT), divided by prior year's SG&A expense relative to assets.
AGE	Natural log of one plus the number of years since the first year that the firm appeared on Compustat.
MARKET_SHARE	Firm sales (Compustat SALE) divided by total sales for the six-digit GICS industry that the firm belongs to.
ROIC	Return on invested capital is calculated by dividing [(EBIT + R&D + 0.5 SG&A – depreciation of R&D and SG&A) × (1 – ETR)] by [Total assets – Cash + undepreciated R&D and SG&A]. SG&A excludes R&D and is amortized over three years. R&D is amortized over five years. ETR is calculated by dividing tax expense (TXT) by pre-tax income, excluding special items. For companies whose ETR cannot be calculated, we assume 35%.

Appendix C: Firms Investigated in Antitrust Cases

This Appendix presents a list of firms investigated by the Antitrust Division of the Department of Justice with available data to calculate internal rate of return.

Industry Sector	**Company Name**	**Industry Based on Six-Digit GICS**
Low-tech	MOLSON COORS BEVERAGE CO	Beverages
	ANHEUSER-BUSCH INBEV	Beverages
	SMITH (A.O.)	Building Products
	MASONITE INTERNATIONAL CORP	Building Products
	BEMIS CO INC	Containers & Packaging
	BLOCK H & R INC	Diversified Consumer Services
	SMITHFIELD FOODS INC	Food Products
	SANFILIPPO JOHN B&SON	Food Products
	DEAN FOODS CO	Food Products
	MAYTAG CORP	Household Durables
	WHIRLPOOL CORP	Household Durables
	ELECTROLUX AB	Household Durables
	UPM-KYMMENE CORP	Paper & Forest Products
Stable-tech	GENERAL DYNAMICS CORP	Aerospace & Defense
	AMERICAN AIRLINES GROUP INC	Airlines
	US AIRWAYS GROUP INC	Airlines
	DELTA AIR LINES INC	Airlines
	UNITED AIRLINES INC	Airlines
	DUPONT DE NEMOURS INC	Chemicals
	MONSANTO CO	Chemicals
	BAKER HUGHES INC	Energy Equipment & Services

Appendix C continued

Industry Sector	Company Name	Industry Based on Six-Digit GICS
Stable-tech	HALLIBURTON CO	Energy Equipment & Services
	HONEYWELL INTERNATIONAL INC	Industrial Conglomerates
	GENERAL ELECTRIC CO	Industrial Conglomerates
	3M CO	Industrial Conglomerates
	DEERE & CO	Machinery
	AGCO CORP	Machinery
	ALCAN INC	Metals & Mining
	ARCELORMITTAL	Metals & Mining
	ATLANTIC RICHFIELD CO	Oil, Gas & Consumable Fuels
	HOLLYFRONTIER CORP	Oil, Gas & Consumable Fuels
Health-high-tech	AETNA INC	Health Care Providers & Services
	CIGNA CORP	Health Care Providers & Services
	HUMANA INC	Health Care Providers & Services
	ANTHEM INC	Health Care Providers & Services
	MERCK & CO	Pharmaceuticals
Digital-high-tech	VERIZON COMMUNICATIONS INC	Diversified Telecommunication Services
	AT&T INC	Diversified Telecommunication Services
	HITACHI LTD	Electronic Equipment, Instruments & Components
	AU OPTRONICS CORP	Electronic Equipment, Instruments & Components
	LIVE NATION ENTERTAINMENT	Entertainment
	AMC ENTERTAINMENT HOLDINGS	Entertainment
	SUNGARD DATA SYSTEMS INC	IT Services
	FIRST DATA CORP	IT Services
	MASTERCARD INC	IT Services
	VISA INC	IT Services

Appendix C continued

Industry Sector	Company Name	Industry Based on Six-Digit GICS
Digital-high-tech	ALPHABET INC	Interactive Media & Services
	BAZAARVOICE INC	Internet Software & Services
	COMCAST CORP	Media
	GRAY TELEVISION INC	Media
	UNIVISION COMMUNICATIONS INC	Media
	NEXSTAR MEDIA GROUP	Media
	APPLIED MATERIALS INC	Semiconductors & Semiconductor Equipment
	INTEL CORP	Semiconductors & Semiconductor Equipment
	MICROSOFT CORP	Software
	ORACLE CORP	Software
	ADOBE INC	Software
	BLACKBOARD INC	Software
	APPLE INC	Technology Hardware, Storage & Peripherals
	3D SYSTEMS CORP	Technology Hardware, Storage & Peripherals
	ALLTEL CORP	Wireless Telecommunication Services

Figure 1
Accounting Rate of Return (ARR) (renders well only in color)

This figure shows accounting rate of return over 1980–2019. Panel A shows the sector-level ARR. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. We calculate the weighted-average ARR (weighted by beginning-of-the-year market value of equity) for each of the four sectors in each year, where ARR is effectively net operating income after taxes divided by beginning assets. Panel B shows the ARR for five tech giants (Apple, Microsoft, Amazon, Alphabet, and Facebook). Amazon's ARRs are -65%, -95%, and -50% in fiscal year 1998, 1999, and 2000, respectively. We set the lower bound of the vertical axis to -50% such that the variations in the ARRs are identifiable in this figure. All numbers used in the calculation are inflation-adjusted to year 2000. Vertical dotted lines separate our study period into different decades: 1980–1989, 1990–1999, 2000–2009, and 2010–2019.

Panel A: Sector-Level ARR

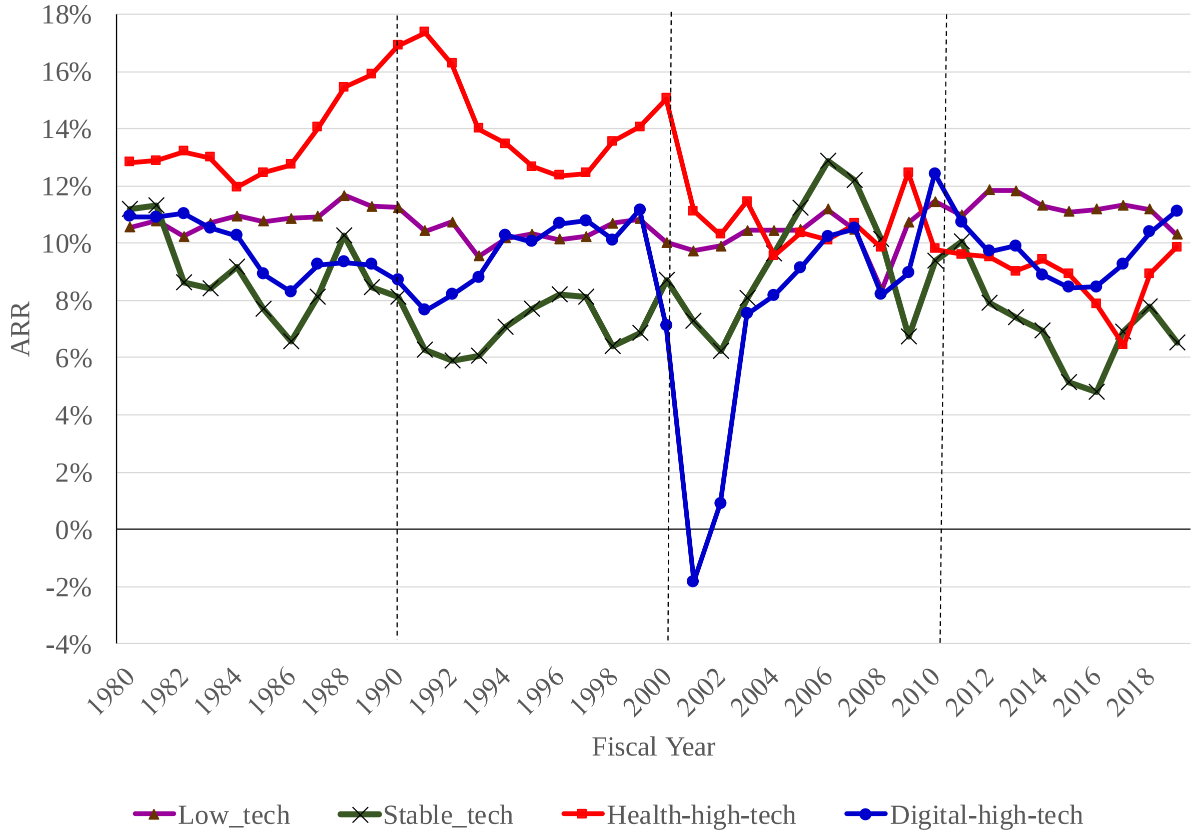

Figure 1. Continued

Panel B: ARR–Tech Giants

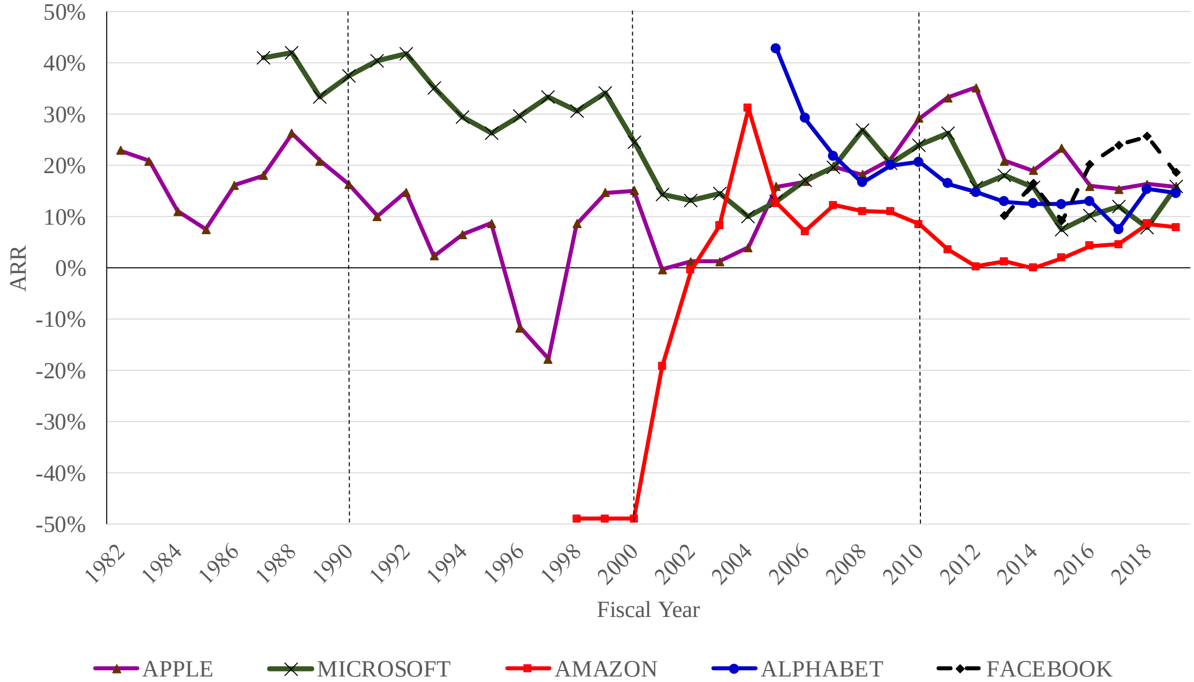

Figure 2
Internal Rate of Return (IRR) (renders well only in color)

This figure shows the internal rate of return over 1980–2019. Panel A shows the sector-level IRR. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. We calculate the weighted-average IRR (weighted by beginning-of-the-year market value of equity) for each of the four sectors in each year. IRR is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile, as described in Section 3. Panel B shows the IRR for five tech giants (Apple, Microsoft, Amazon, Alphabet, and Facebook). All numbers used in the calculation are inflation-adjusted to year 2000. Vertical dotted lines separate our study period into different decades: 1980–1989, 1990–1999, 2000–2009, and 2010–2019.

Panel A: Sector-Level IRR

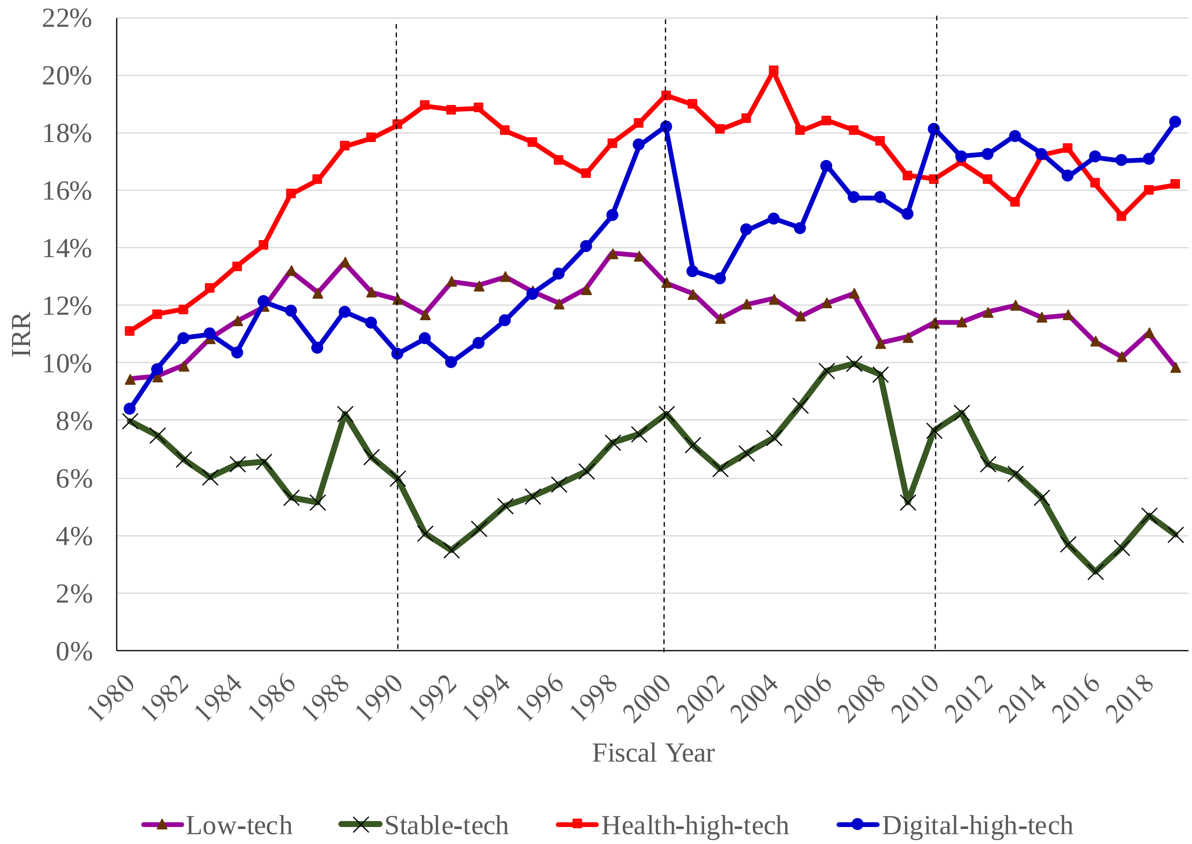

Figure 2. continued

Panel B: IRR–Tech Giants

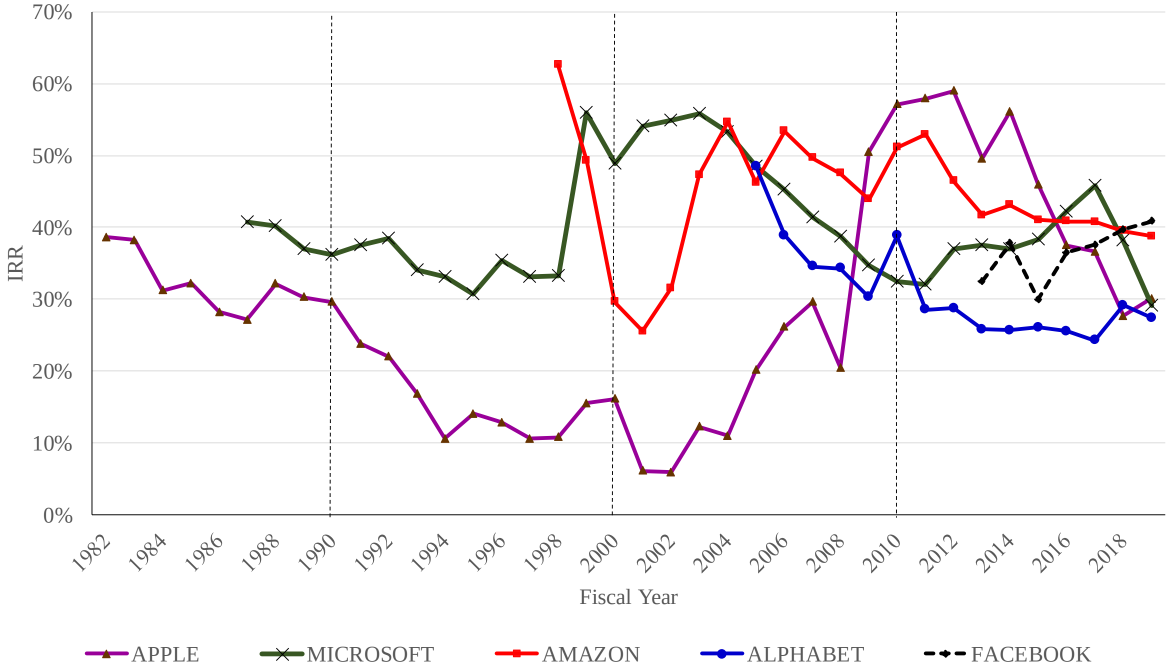

Figure 3
Contribution of Industry Sectors to Top 100 Internal Rate of Return (IRR) Firms (renders well only in color)

This figure shows the contribution of industry sectors to top 100 firms by internal rate of return over 1980–2019. Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. IRR is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile, as described in Section 3. Data are presented by the decades: 1980–1989, 1990–1999, 2000–2009, and 2010–2019.

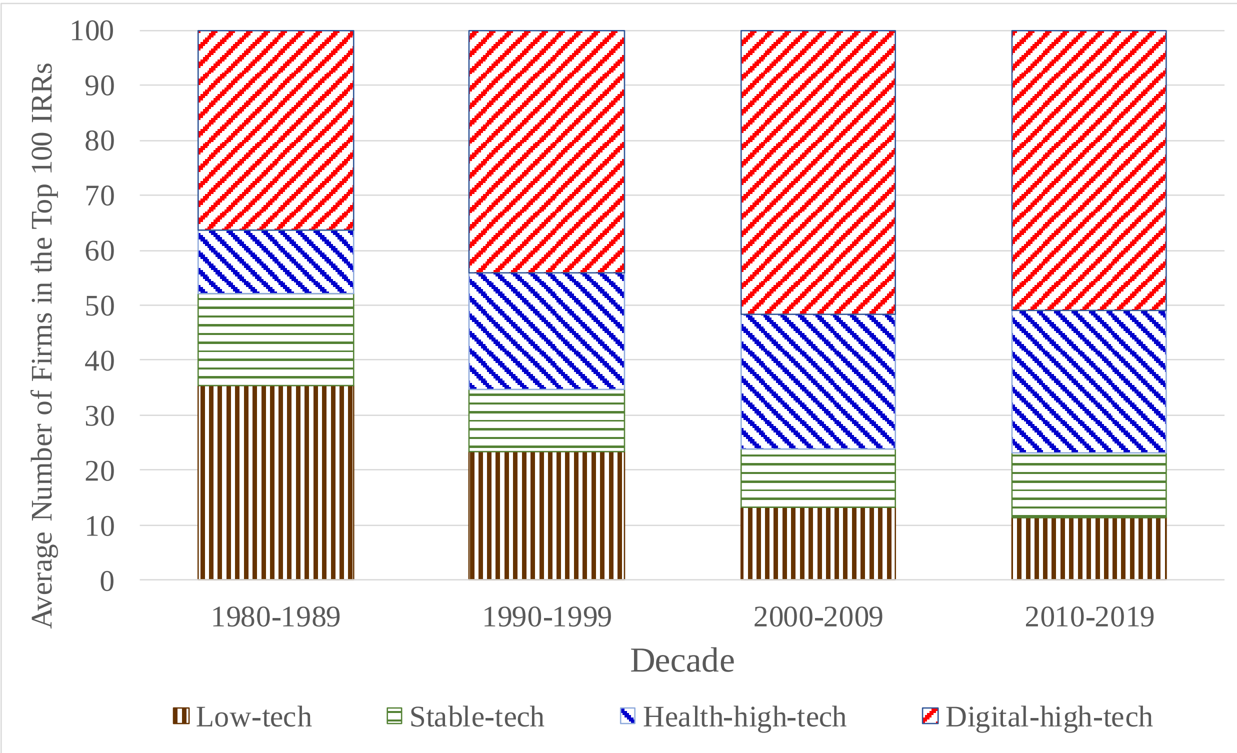

Figure 4
Return on Invested Capital (ROIC) (renders well only in color)

This figure shows the return on invested capital (ROIC) over 1980–2019. Panel A shows the sector-level ROIC. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. We calculate the weighted-average ROIC (weighted by beginning-of-the-year market value of equity) for each of the four sectors in each year. ROIC is calculated by modifying the numerator and denominator of the ratio of net income to average total assets. After-tax tax impact of net investment in intangibles is added to numerator. Net investment is obtained by subtracting depreciation of intangible stock [assuming three- and five-year lives for research and development (R&D) and selling, general, and administrative (SG&A) investment, respectively] from current R&D plus 50% of SG&A (excluding R&D). In the denominator, we add capital stock of intangible investment and subtract cash, assuming that it is not an operating investment. Panel B shows the ROICs for five tech giants (Apple, Microsoft, Amazon, Alphabet, and Facebook). Microsoft's ROICs are 66%, and 58% in fiscal year 1987, and 1988, respectively. Alphabet's ROICs are 92%, 96%, and 51% in fiscal year 2005, 2006, and 2007, respectively. We set the upper bound of the ROICs to 50% such that the variations in the ROICs are identifiable in this figure. All numbers used in the calculation are inflation-adjusted to year 2000. Vertical dotted lines separate our study period into different decades: 1980–1989, 1990–1999, 2000–2009, and 2010–2019.

Panel A: Sector-Level ROICs

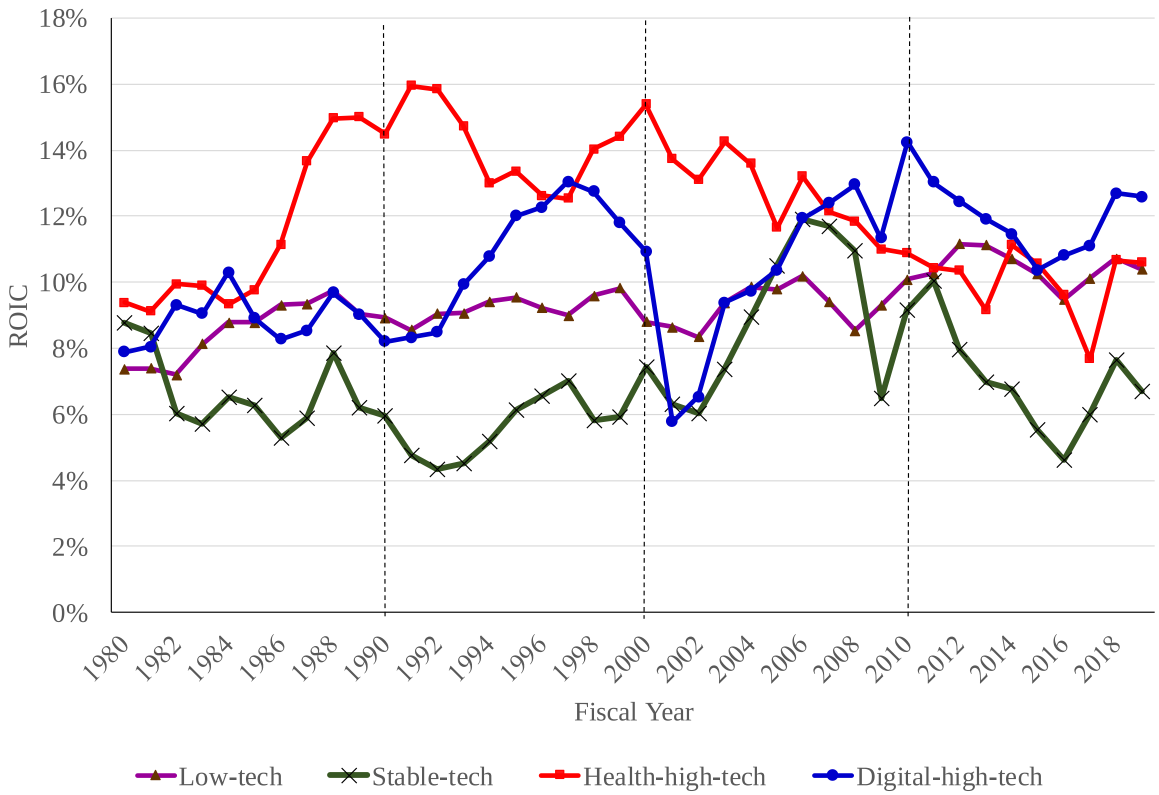

Figure 4. Continued

Panel B: ROICs–Tech Giants

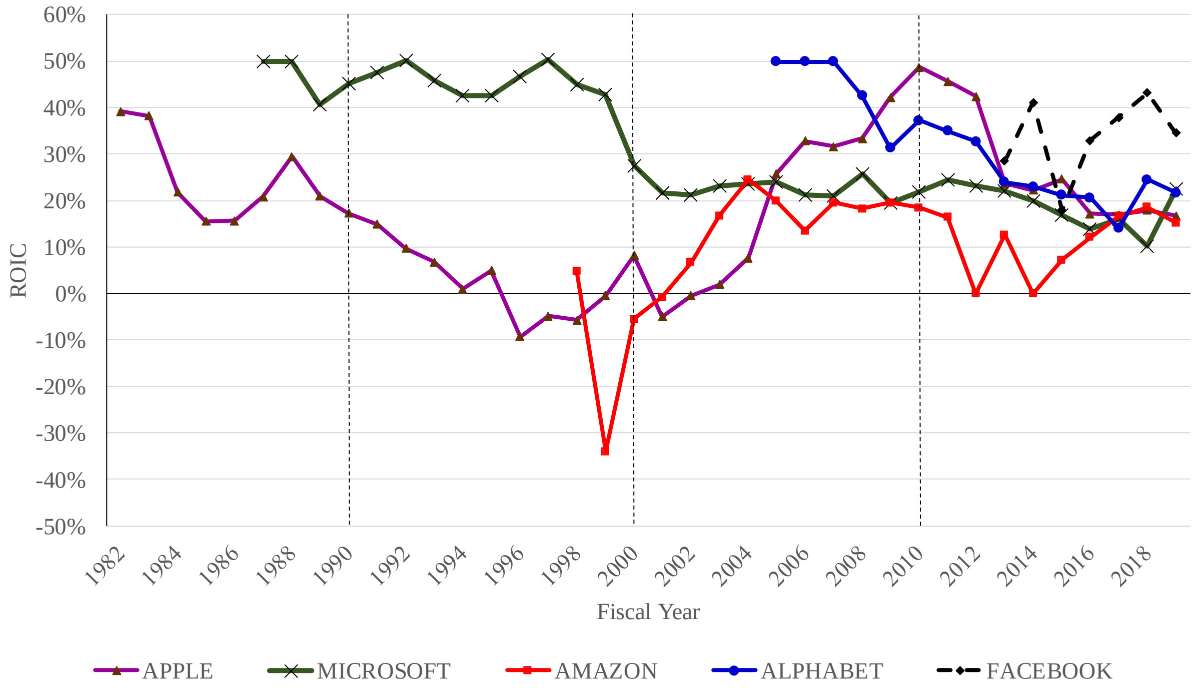

Table 1
Sample Selection and Summary Statistics

This table presents the selection steps for our sample firms over 1980–2019. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). See Appendix B for variable definitions. CRSP = Center for Research in Security Prices; GICS = Global Industry Classification Standard.

Selection Step	**Observations**
Firm-year observations covered by Compustat for fiscal years 1980 through 2019	372,765
Less observations:	
Utilities, financials, and real estate firms and firms with missing GICS code	113,571
Without CRSP coverage or with fiscal year end date before CRSP began listing date of stock data	83,337
With inflation-adjusted assets less than $100 million	75,086
Subtotal: Prior to data requirements	100,771
Less observations:	
Insufficient data to calculate cash recovery rate or accounting rate of return	1,005
Firms with insufficient number of years (require at least six years)	9,543
Missing beginning market value of equity	2,636
Total Firm-Years	**87,587**
Total Firms	**6,570**

Table 2
Frequency Distribution and 75th Percentile of Inflation-Adjusted Assets

This table shows the number of firms with inflation-adjusted assets exceeding $100 million (Panel A) and the 75th percentile of inflation-adjusted assets by sector and year (Panel B) over 1980–2019. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. All numbers used in the calculation are inflation-adjusted to year 2000.

Panel A: Number of Firms with Inflation-Adjusted Assets in Excess of $100 Million

Fiscal Year	Low-Tech	Stable-Tech	Health-High-Tech	Digital-High-Tech	Total
1980	599	502	67	180	1,348
1981	604	515	68	191	1,378
1982	617	525	80	210	1,432
1983	641	534	85	250	1,510
1984	692	558	105	291	1,646
1985	719	571	115	313	1,718
1986	703	537	131	327	1,698
1987	716	541	143	350	1,750
1988	721	532	145	354	1,752
1989	701	555	146	365	1,767
1990	699	568	149	364	1,780
1991	703	582	154	369	1,808
1992	734	599	184	371	1,888
1993	794	631	198	406	2,029
1994	891	683	206	447	2,227
1995	940	716	221	490	2,367
1996	965	739	251	564	2,519
1997	990	770	264	646	2,670
1998	1,000	773	262	682	2,717
1999	995	755	262	712	2,724
2000	952	713	280	804	2,749
2001	905	681	305	829	2,720
2002	884	668	321	795	2,668
2003	858	669	330	804	2,661
2004	835	678	333	827	2,673
2005	821	686	329	821	2,657
2006	802	720	325	798	2,645
2007	768	705	332	758	2,563
2008	737	723	325	741	2,526
2009	722	718	316	698	2,454

Table 2 continued

Fiscal Year	Low-Tech	Stable-Tech	Health-High-Tech	Digital-High-Tech	Total
2010	723	735	317	689	2,464
2011	717	722	298	689	2,426
2012	709	732	280	680	2,401
2013	700	731	271	670	2,372
2014	703	732	283	669	2,387
2015	694	687	285	655	2,321
2016	669	687	276	600	2,232
2017	634	679	263	574	2,150
2018	609	644	257	544	2,054
2019	473	577	231	455	1,736
Total	**30,339**	**26,073**	**9,193**	**21,982**	**87,587**

Panel B: Inflation-Adjusted Assets at 75th Percentile (in Millions)

Fiscal Year	Low-Tech	Stable-Tech	Health-High-Tech	Digital-High-Tech
1980	1,090	2,281	3,332	1,381
1981	1,063	2,115	3,503	1,411
1982	1,043	2,155	3,216	1,429
1983	1,133	2,105	2,700	1,125
1984	1,082	2,157	2,386	1,030
1985	1,199	2,074	1,959	1,158
1986	1,256	2,260	1,730	1,358
1987	1,255	2,189	1,481	1,398
1988	1,208	2,379	1,461	1,596
1989	1,283	2,138	1,144	1,564
1990	1,259	2,232	1,159	1,558
1991	1,340	2,164	1,110	1,817
1992	1,340	2,209	1,028	1,837
1993	1,292	2,245	995	1,741
1994	1,222	2,097	1,219	1,767
1995	1,179	2,059	1,362	1,731
1996	1,269	2,212	1,316	1,652
1997	1,332	2,160	1,337	1,766
1998	1,517	2,356	1,626	1,708
1999	1,630	2,736	1,556	1,824
2000	1,633	2,765	1,622	2,067
2001	1,716	2,959	1,752	2,094
2002	1,879	3,077	1,781	2,134
2003	2,138	3,421	1,852	2,152
2004	2,380	3,688	1,903	2,175
2005	2,412	3,875	2,047	2,042

Table 2 continued

Fiscal Year	Low-Tech	Stable-Tech	Health-High-Tech	Digital-High-Tech
2006	2,339	3,912	2,013	2,138
2007	2,484	4,065	1,906	2,398
2008	2,346	4,136	2,057	2,287
2009	2,406	3,959	2,024	2,460
2010	2,664	4,320	2,370	2,624
2011	2,602	4,805	2,363	2,688
2012	2,871	5,249	3,138	2,688
2013	3,017	5,424	3,110	2,964
2014	3,176	5,890	3,735	3,478
2015	3,285	5,904	3,781	3,691
2016	3,351	6,206	4,328	4,481
2017	3,641	6,425	5,361	5,026
2018	3,648	6,398	4,598	5,760
2019	4,047	6,558	4,995	6,022

Table 3
Summary Statistics

This table presents summary statistics for our sample firms over 1980–2019. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000), as described in Tables 1 and 2. *ARR* is effectively net operating income after taxes divided by beginning assets. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile, as described in Section 3. See Appendix B for variable definitions.

Variable	***N***	**Mean**	**Std Dev**	**25th Pctl**	**Median**	**75th Pctl**
IRR	87,587	0.117	0.113	0.050	0.108	0.171
ARR	87,587	0.064	0.098	0.032	0.071	0.110
CRR	87,587	0.193	0.112	0.125	0.171	0.229
CF	87,587	984	2,640	69	175	600
INVESTMENT	87,587	6,363	17,215	432	1,069	3,745
G_ANN	87,587	1.112	0.262	0.986	1.050	1.150
G_GEOM	87,587	1.108	0.118	1.032	1.079	1.157
AT	87,587	4,081	11,063	253	676	2,400
OIBDP	87,587	549	1,536	27	85	320
XRD	49,426	150	491	2	17	65
XSGA	80,173	602	1,546	50	124	388
TXT	87,587	94	293	1	12	51
TXDC	83,521	2	57	-2	0	4
ACT	84,561	1,299	3,242	116	269	870
CHE	87,573	371	1,062	16	59	205
LCT	84,994	950	2,709	52	134	503
PPEGT	87,172	2,493	7,417	98	307	1,282
PPENT	87,467	1,348	3,880	50	165	719
IB	87,587	186	622	3	24	106
MII	75,165	6	29	0	0	0
XINT	83,671	71	171	3	12	51
SPPE	65,046	14	50	0	0	4
SIV	81,966	85	415	0	0	2
MVE	87,587	3,761	10,578	194	586	2,137

Table 4
Firm-Level Accounting Rate of Return (ARR) and Internal Rate of Return (IRR)

This table presents statistics for firm-level accounting rate of return and internal rate of return for our sample firms over 1980–2019. Panel A shows mean, median, and standard deviation of ARR and IRR as well as the Spearman correlation between ARR and IRR. Panel B shows the average number of firms in the top 100 IRRs by decade. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. *ARR* is effectively net operating income after taxes divided by beginning assets. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile, as described in Section 3. All numbers used in the calculation are inflation-adjusted to year 2000. *Corr(ARR*, *IRR)* is the Spearman correlations between *ARR* and *IRR*. Correlations are all significantly different from zero at 1% level or better (in bold).

Panel A: Summary Statistics and Spearman Correlation between *ARR* and *IRR*

Sector	*N*	Variable	Mean	Median	Std Dev
Low-tech	30,339	*ARR*	0.077	0.077	0.078
		IRR	0.117	0.114	0.094
		Corr(ARR, IRR)		***0.487***	
Stable-tech	26,073	*ARR*	0.067	0.070	0.080
		IRR	0.074	0.071	0.099
		Corr(ARR, IRR)		***0.519***	
Health-high-tech	9,193	*ARR*	0.047	0.073	0.139
		IRR	0.168	0.155	0.125
		Corr(ARR, IRR)		***0.321***	
Digital-high-tech	21,982	*ARR*	0.050	0.061	0.118
		IRR	0.149	0.130	0.127
		Corr(ARR, IRR)		***0.350***	

Panel B: Average Number of Firms in the Top 100 *IRR*s by Decade

Sector	1980–1989	1990–1999	2000–2009	2010–2019
Low-tech	35	23	13	11
Stable-tech	17	11	11	12
Health-high-tech	12	21	25	26
Digital-high-tech	36	44	52	51

Table 5
Sector-Level Accounting Rate of Return (ARR) and Internal Rate of Return (IRR)

This table presents sector-level accounting rate of return and internal rate of return over our study period of 1980–2019. Panel A presents ARR and IRR by year for each sector. Panel B summarizes the comparison between the sector-level IRR and the sector-level ARR in each decade: 1980–1989, 1990–1999, 2000–2009, and 2010–2019. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile, as described in Section 3. *ARR* is effectively net operating income after taxes divided by beginning assets. Sector-level *IRR*s or *ARR*s are weighted-average *IRR*s or *ARR*s (weighted by beginning-of-the-year market value of equity) calculated each year for each sector. All numbers used in the calculation are inflation-adjusted to year 2000.

Panel A: Sector-Level *ARR* and *IRR*

Fiscal Year	Low-Tech		Stable-Tech		Health-High-Tech		Digital-High-Tech	
	ARR	***IRR***	***ARR***	***IRR***	***ARR***	***IRR***	***ARR***	***IRR***
1980	11%	9%	11%	8%	13%	11%	11%	8%
1981	11%	10%	11%	7%	13%	12%	11%	10%
1982	10%	10%	9%	7%	13%	12%	11%	11%
1983	11%	11%	8%	6%	13%	13%	11%	11%
1984	11%	11%	9%	6%	12%	13%	10%	10%
1985	11%	12%	8%	7%	12%	14%	9%	12%
1986	11%	13%	7%	5%	13%	16%	8%	12%
1987	11%	12%	8%	5%	14%	16%	9%	11%
1988	12%	14%	10%	8%	15%	18%	9%	12%
1989	11%	12%	8%	7%	16%	18%	9%	11%
1990	11%	12%	8%	6%	17%	18%	9%	10%
1991	10%	12%	6%	4%	17%	19%	8%	11%
1992	11%	13%	6%	3%	16%	19%	8%	10%
1993	10%	13%	6%	4%	14%	19%	9%	11%
1994	10%	13%	7%	5%	13%	18%	10%	11%
1995	10%	13%	8%	5%	13%	18%	10%	12%
1996	10%	12%	8%	6%	12%	17%	11%	13%
1997	10%	13%	8%	6%	12%	17%	11%	14%
1998	11%	14%	6%	7%	14%	18%	10%	15%
1999	11%	14%	7%	8%	14%	18%	11%	18%
2000	10%	13%	9%	8%	15%	19%	7%	18%
2001	10%	12%	7%	7%	11%	19%	-2%	13%
2002	10%	12%	6%	6%	10%	18%	1%	13%
2003	10%	12%	8%	7%	11%	18%	8%	15%
2004	10%	12%	10%	7%	10%	20%	8%	15%
2005	10%	12%	11%	9%	10%	18%	9%	15%

Table 5 continued

Fiscal Year	Low-Tech		Stable-Tech		Health-High-Tech		Digital-High-Tech	
	ARR	***IRR***	***ARR***	***IRR***	***ARR***	***IRR***	***ARR***	***IRR***
2006	11%	12%	13%	10%	10%	18%	10%	17%
2007	10%	12%	12%	10%	11%	18%	11%	16%
2008	8%	11%	10%	10%	10%	18%	8%	16%
2009	11%	11%	7%	5%	12%	17%	9%	15%
2010	11%	11%	9%	8%	10%	16%	12%	18%
2011	11%	11%	10%	8%	10%	17%	11%	17%
2012	12%	12%	8%	6%	10%	16%	10%	17%
2013	12%	12%	7%	6%	9%	16%	10%	18%
2014	11%	12%	7%	5%	9%	17%	9%	17%
2015	11%	12%	5%	4%	9%	17%	8%	16%
2016	11%	11%	5%	3%	8%	16%	8%	17%
2017	11%	10%	7%	4%	6%	15%	9%	17%
2018	11%	11%	8%	5%	9%	16%	10%	17%
2019	10%	10%	7%	4%	10%	16%	11%	18%

Panel B: Comparison of Sector-Level *ARR* and *IRR* by Decade

Sector	Variable	1980–1989	1990–1999	2000–2009	2010–2019
Low-tech	*IRR*	11.5%	12.7%	11.9%	11.2%
(*N* = 40)	*ARR*	10.9%	10.4%	10.2%	11.2%
	IRR minus *ARR*	0.6%	2.3%***	1.7%***	-0.1%
	[t-stat]	*[1.55]*	*[9.58]*	*[6.64]*	*[-0.51]*
Stable-tech	*IRR*	6.7%	5.5%	7.9%	5.3%
(*N* = 40)	*ARR*	9.0%	7.1%	9.3%	7.3%
	IRR minus *ARR*	-2.3%***	-1.6%***	-1.4%***	-2.0%***
	[t-stat]	*[-8.46]*	*[-4.00]*	*[-3.94]*	*[-9.04]*
Health-high-tech	*IRR*	14.2%	18.0%	18.4%	16.4%
(*N* = 40)	*ARR*	13.4%	14.3%	11.1%	8.9%
	IRR minus *ARR*	0.8%	3.7%***	7.3%***	7.4%***
	[t-stat]	*[1.40]*	*[8.61]*	*[12.05]*	*[26.95]*
Digital-high-tech	*IRR*	10.8%	12.6%	15.2%	17.4%
(*N* = 40)	*ARR*	9.9%	9.6%	6.9%	9.9%
	IRR minus *ARR*	0.9%	2.9%***	8.3%***	7.5%***
	[t-stat]	*[1.51]*	*[5.59]*	*[8.09]*	*[25.43]*

Table 6
Tech Giants

This table presents the accounting rate of return (ARR) in Panel A, internal rate of return (IRR) in Panel B, and weighted-average cost of capital (WACC) in Panel C for five tech giants (Apple, Microsoft, Amazon, Alphabet, and Facebook) over our study period of 1980–2019 separated by decade: 1980–1989, 1990–1999, 2000–2009, and 2010–2019. *ARR* is effectively net operating income after taxes divided by beginning assets. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile. Estimation procedures for *ARR*, *IRR*, and *WACC* are described in Section 3.

Panel A: *ARR*

Fiscal Year	Apple	Microsoft	Amazon	Alphabet	Facebook
1982	23%				
1983	21%				
1984	11%				
1985	8%				
1986	16%				
1987	18%	41%			
1988	26%	42%			
1989	21%	33%			
1990	16%	37%			
1991	10%	40%			
1992	15%	42%			
1993	2%	35%			
1994	7%	29%			
1995	9%	26%			
1996	-12%	30%			
1997	-18%	33%			
1998	9%	31%	-65%		
1999	15%	34%	-95%		
2000	15%	24%	-50%		
2001	0%	14%	-19%		
2002	1%	13%	0%		
2003	1%	14%	8%		
2004	4%	10%	31%		
2005	16%	13%	13%	43%	
2006	17%	17%	7%	29%	
2007	20%	20%	12%	22%	
2008	18%	27%	11%	17%	
2009	21%	20%	11%	20%	
2010	29%	24%	8%	21%	
2011	33%	26%	4%	16%	
2012	35%	16%	0%	15%	
2013	21%	18%	1%	13%	10%
2014	19%	16%	0%	13%	16%
2015	23%	8%	2%	12%	9%
2016	16%	10%	4%	13%	20%
2017	15%	12%	5%	7%	24%
2018	16%	8%	9%	15%	26%
2019	16%	16%	8%	15%	19%

Table 6 continued

Panel B: *IRR*

Fiscal Year	Apple	Microsoft	Amazon	Alphabet	Facebook
1982	39%				
1983	38%				
1984	31%				
1985	32%				
1986	28%				
1987	27%	41%			
1988	32%	40%			
1989	30%	37%			
1990	30%	36%			
1991	24%	38%			
1992	22%	39%			
1993	17%	34%			
1994	11%	33%			
1995	14%	31%			
1996	13%	35%			
1997	11%	33%			
1998	11%	33%	63%		
1999	15%	56%	49%		
2000	16%	49%	30%		
2001	6%	54%	26%		
2002	6%	55%	32%		
2003	12%	56%	47%		
2004	11%	53%	55%		
2005	20%	49%	46%	49%	
2006	26%	45%	53%	39%	
2007	30%	41%	50%	35%	
2008	20%	39%	48%	34%	
2009	50%	35%	44%	30%	
2010	57%	32%	51%	39%	
2011	58%	32%	53%	29%	
2012	59%	37%	46%	29%	
2013	50%	38%	42%	26%	32%
2014	56%	37%	43%	26%	38%
2015	46%	38%	41%	26%	30%
2016	37%	42%	41%	25%	36%
2017	37%	46%	41%	24%	38%
2018	28%	38%	39%	29%	40%
2019	30%	29%	39%	27%	41%

Table 6 continued

Panel C: ***WACC***

Tech Giant	1980–1989	1990–1999	2000–2009	2010–2019
Apple	17.5%	10.3%	10.2%	7.4%
Microsoft	13.8%	11.6%	9.0%	7.6%
Amazon		10.1%	10.6%	8.5%
Alphabet			8.5%	8.2%
Facebook				8.8%

Table 7
Tobin's Q

This table presents the average Tobin's Q by four sectors and decades (1980–1989, 1990–1999, 2000–2009, and 2010–2019) in Panel A. Panels B–E estimate a regression of Tobin's Q on accounting rate of return (ARR) and internal rate of return (IRR) by four sectors and decades. Our sample consists of firms with inflation-adjusted total assets exceeding $100 million (inflation-adjusted to year 2000). Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. Tobin's Q is calculated as the market value of the firm divided by the book value of total assets, and it is calculated for firms with positive shareholders' equity. *ARR* is effectively net operating income after taxes divided by beginning assets. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile, as described in Section 3. All numbers used in the calculation are inflation-adjusted to year 2000. Regressions include year fixed effects. *t*-statistics in brackets are based on standard errors clustered by firm. All regression variables are defined in Appendix B. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, on a two-tailed basis.

Panel A: Average Tobin's Q

Sector	**Tobin's Q**	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
Low-tech	*N*	6,633	8,450	8,034	6,257
	Mean	1.340	1.590	1.630	1.800
Stable-tech	*N*	5,280	6,637	6,760	6,721
	Mean	1.230	1.430	1.500	1.510
Health-high-tech	*N*	1,070	2,117	3,080	2,632
	Mean	1.790	2.420	2.420	2.560
Digital-high-tech	*N*	2,774	4,802	7,551	5,908
	Mean	1.600	2.310	1.970	2.050
Tech giants	*N*	11	22	30	47
	Mean	3.936	6.346	4.594	3.851

Table 7 continued

Panel B: Low-Tech

Variable	1980–1989	1990–1999	2000–2009	2010–2019
IRR	1.213***	2.060***	2.598***	2.981***
	[7.79]	[11.64]	[11.23]	[8.50]
ARR	5.066***	5.493***	5.384***	6.798***
	[12.54]	[13.08]	[15.93]	[15.06]
Difference in coefficients on				
ARR and *IRR*	-3.853***	-3.433***	-2.786***	-3.817***
[f-stat]	[67.95]	[50.95]	[50.39]	[39.99]
Observations	6,633	8,450	8,034	6,257
Adjusted R-squared	0.3773	0.3232	0.3740	0.4076

Panel C: Stable-Tech

Variable	1980–1989	1990–1999	2000–2009	2010–2019
IRR	1.056***	0.902***	0.929***	1.828***
	[6.49]	[4.82]	[4.77]	[6.06]
ARR	2.978***	3.626***	2.720***	3.125***
	[9.37]	[12.00]	[8.31]	[7.64]
Difference in coefficients on				
ARR and *IRR*	-1.922***	-2.724***	-1.791***	-1.297**
[f-stat]	[27.15]	[63.41]	[19.32]	[4.76]
Observations	5,280	6,637	6,760	6,721
Adjusted R-squared	0.2525	0.2276	0.2025	0.2232

Table 7 continued

Panel D: Health-High-Tech

Variable	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
IRR	2.114***	2.755***	2.784***	4.693***
	[3.10]	[6.69]	[8.55]	[9.21]
ARR	3.889***	1.591***	0.494	-1.326**
	[3.25]	[2.71]	[1.37]	[-2.47]
Difference in coefficients on				
ARR and *IRR*	-1.775	-4.346	2.290***	6.019***
[f-stat]	[1.21]	[2.69]	[20.33]	[63.30]
Observations	1,070	2,117	3,080	2,632
Adjusted *R*-squared	0.2030	0.1057	0.1284	0.1495

Panel E: Digital-High-Tech

Variable	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
IRR	2.345***	4.724***	3.201***	5.415***
	[9.56]	[17.20]	[17.62]	[16.95]
ARR	3.654***	4.242***	2.764***	1.280***
	[9.74]	[12.40]	[13.11]	[3.13]
Difference in coefficients on				
ARR and *IRR*	-1.309***	0.482	0.437	4.135***
[f-stat]	[7.46]	[1.04]	[2.59]	[46.82]
Observations	2,774	4,802	7,551	5,908
Adjusted *R*-squared	0.3126	0.3934	0.2937	0.3123

Table 8
Average Internal Rate of Return (IRR) Five Years During and Before Department of Justice (DOJ) Investigation

This table shows the average internal rate of return (IRR) for 55 firms investigated by the DOJ Antitrust Division in the five years during and before the probe. For multiple investigations for the same company or investigations over multiple years, we use data for the five years preceding (and inclusive of the first year) the first case investigated. Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile. Its estimation procedure is described in Section 3.

Industry Sector	**Number of Firms**	***IRR***
Low-tech	11	7.3%
Stable-tech	16	8.0%
Health-high-tech	4	17.7%
Digital-high-tech	24	18.3%
All	55	13.0%

Table 9
Determinants of Difference Between Accounting Rate of Return (ARR) and Internal Rate of Return (IRR)

This table examines the factors that are associated with difference between accounting rate of return and internal rate of return. *ARR* is effectively net operating income after taxes divided by beginning assets. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile. Its estimation procedure is described in Section 3. The dependent variable is (*IRR* – *ARR*). All regression variables are defined in Appendix B. Regressions include year fixed effects. *t*-statistics in brackets are based on standard errors clustered by firm. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, on a two-tailed basis.

Panel A: Low-Tech

Variable	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
INVENTORY	0.032**	0.003	0.018	0.015
	[2.05]	[0.21]	[1.36]	[0.91]
PPE	0.013	-0.012	-0.012	-0.008
	[1.17]	[-1.07]	[-1.21]	[-0.63]
INTANGIBLES_BS	0.079***	0.048***	0.019***	0.013
	[4.37]	[4.40]	[2.64]	[1.43]
RD_INTENSITY	0.500***	0.552***	0.671***	0.310
	[3.41]	[4.06]	[4.81]	[1.65]
SGA_INTENSITY	0.178***	0.194***	0.195***	0.207***
	[10.31]	[10.38]	[13.55]	[13.23]
LOSS	0.042***	0.076***	0.072***	0.068***
	[7.86]	[17.06]	[16.99]	[13.94]
RD_GROWTH	-0.011***	-0.021***	-0.030***	-0.017***
	[-3.54]	[-4.77]	[-7.94]	[-3.62]
SGA_GROWTH	0.026***	0.031***	0.039***	0.011
	[3.95]	[4.54]	[6.30]	[1.44]
AGE	-0.020***	-0.027***	-0.024***	-0.026***
	[-7.31]	[-11.52]	[-10.43]	[-7.15]
MARKET_SHARE	-0.055	-0.052	0.004	-0.048
	[-1.41]	[-1.07]	[0.11]	[-0.98]
Observations	6,706	8,699	8,199	6,570
Adjusted *R*-squared	0.2041	0.2522	0.2873	0.2698

Table 9 continued

Panel B: Stable-Tech

Variable	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
INVENTORY	0.031	-0.046*	-0.044	-0.037
	[1.58]	[-1.85]	[-1.36]	[-1.23]
PPE	-0.002	-0.028*	0.006	-0.016
	[-0.12]	[-1.76]	[0.33]	[-1.06]
INTANGIBLES_BS	0.158***	0.046***	0.015	0.019*
	[5.05]	[3.61]	[1.24]	[1.71]
RD_INTENSITY	0.393***	0.552***	0.108	0.416***
	[3.17]	[3.80]	[0.78]	[3.75]
SGA_INTENSITY	0.171***	0.196***	0.248***	0.156***
	[6.46]	[7.52]	[7.57]	[5.12]
LOSS	0.045***	0.055***	0.068***	0.045***
	[9.72]	[11.43]	[13.18]	[9.35]
RD_GROWTH	0.003	-0.006	-0.000	-0.010**
	[0.72]	[-1.33]	[-0.08]	[-2.30]
SGA_GROWTH	0.006	0.001	0.003	0.005
	[1.00]	[0.12]	[0.56]	[0.75]
AGE	-0.019***	-0.020***	-0.021***	-0.023***
	[-6.08]	[-7.88]	[-7.78]	[-7.36]
MARKET_SHARE	0.029	0.080	0.017	0.005
	[0.57]	[0.67]	[0.19]	[0.07]
Observations	5,364	6,803	6,927	6,882
Adjusted *R*-squared	0.1640	0.1568	0.1650	0.1411

Table 9 continued

Panel C: Health-High-Tech

Variable	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
INVENTORY	0.045	-0.157***	-0.085**	-0.062
	[0.86]	[-3.22]	[-2.18]	[-1.12]
PPE	-0.004	-0.189***	-0.173***	-0.114***
	[-0.09]	[-5.03]	[-6.08]	[-3.11]
INTANGIBLES_BS	0.140***	-0.009	-0.008	-0.016
	[3.03]	[-0.42]	[-0.61]	[-1.09]
RD_INTENSITY	0.090	0.146***	0.173***	0.315***
	[1.09]	[3.19]	[5.18]	[7.84]
SGA_INTENSITY	0.142***	0.039	0.040	0.082***
	[3.70]	[0.88]	[1.38]	[2.64]
LOSS	0.100***	0.128***	0.129***	0.103***
	[6.63]	[11.17]	[12.80]	[11.05]
RD_GROWTH	-0.014	-0.013	0.010	0.003
	[-1.51]	[-1.39]	[1.43]	[0.40]
SGA_GROWTH	0.011	0.036***	0.003	0.019
	[0.78]	[2.66]	[0.33]	[1.24]
AGE	-0.044***	-0.037***	-0.029***	-0.046***
	[-6.43]	[-7.04]	[-4.85]	[-6.23]
MARKET_SHARE	0.002	-0.073	-0.093	0.125
	[0.03]	[-0.71]	[-0.86]	[1.28]
Observations	1,070	2,127	3,080	2,645
Adjusted R-squared	0.3038	0.3271	0.3988	0.4962

Table 9 continued

Panel D: Digital-High-Tech

Variable	**1980–1989**	**1990–1999**	**2000–2009**	**2010–2019**
INVENTORY	0.058**	0.034	-0.028	-0.031
	[2.53]	[1.34]	[-0.88]	[-0.70]
PPE	0.031**	-0.061***	-0.082***	-0.113***
	[1.99]	[-3.72]	[-5.30]	[-5.28]
INTANGIBLES_BS	0.013	0.007	-0.000	-0.037***
	[0.57]	[0.51]	[-0.05]	[-3.15]
RD_INTENSITY	0.376***	0.476***	0.216***	0.307***
	[5.66]	[11.31]	[6.30]	[8.13]
SGA_INTENSITY	0.176***	0.150***	0.199***	0.251***
	[6.62]	[6.59]	[9.38]	[10.83]
LOSS	0.088***	0.118***	0.092***	0.078***
	[11.22]	[17.65]	[18.95]	[13.50]
RD_GROWTH	0.005	0.007	0.032***	0.006
	[0.82]	[1.29]	[6.05]	[0.88]
SGA_GROWTH	0.009	0.013*	0.026***	0.017*
	[0.99]	[1.88]	[4.26]	[1.83]
AGE	-0.033***	-0.033***	-0.024***	-0.040***
	[-8.23]	[-9.30]	[-6.01]	[-7.54]
MARKET_SHARE	-0.053	-0.051	0.122	0.313***
	[-1.50]	[-0.71]	[1.20]	[3.18]
Observations	2,813	5,033	7,805	6,127
Adjusted *R*-squared	0.3864	0.3945	0.3430	0.4043

Table 10
Sensitivity Analyses for the Calculation of Internal Rate of Return (IRR)

This table presents internal rate of return calculated under different sets of assumption. *IRR* is defined as the discount rate that equates the initial investment with related cash payouts and is estimated under a representative cash payout profile. Its estimation procedure is described in Section 3. In the base case, *IRR* is calculated by capitalizing 100% of research and development (R&D) and 50% of non-R&D selling, general, and administrative (SG&A) expenses, while assuming a payback period of nine years and a gestational lag of three years (Q1 profile; Fisher and McGowan 1983). In this table, we calculate *IRR* by making alternative assumptions. *IRR_N4* is calculated with a payback assumption of four years. *IRR_Q2* is the *IRR* under Q2 profile that assumes no gestational lag in payback. *IRR_50RD_25SGA* is calculated by capitalizing 50% of R&D and 25% of non-R&D SG&A. We require non-missing values for all three alternative versions of *IRR* in this analysis. Panel A presents summary statistics, and Panel B presents rank correlations among *IRR*s calculated under different sets of assumptions. Correlations are all significantly different from zero at the 1% level or better. Panel C presents sector-level *IRR*s under different assumptions for four industry sectors. Firms are classified into one of the four industry sectors: low-technology, stable-technology, health-high-technology, and digital-high-technology, based on the first six digits of their Global Industry Classification Standard codes, as described in Appendix A.

Panel A: Descriptive Statistics

Payout Period	Cash Payout Profile	R&D and SG&A Capitalization	Variable	*N*	Mean	Std Dev	25th Pctl	Median	75th Pctl
Base Case									
Nine years	Q1	100% R&D, 50% SG&A	*IRR*	86,571	0.119	0.110	0.051	0.109	0.171
Sensitivity Analysis									
Four years	Q1	100% R&D, 50% SG&A	*IRR_N4*	86,571	-0.032	0.172	-0.138	-0.046	0.052
Nine years	Q2	100% R&D, 50% SG&A	*IRR_Q2*	86,571	0.124	0.125	0.048	0.113	0.183
Nine years	Q1	50% R&D, 25% SG&A	*IRR_50RD_25SGA*	86,571	0.097	0.115	0.029	0.085	0.150

Table 10 continued

Panel B: Spearman Correlation

	IRR_N4	*IRR_Q2*	*IRR_50RD_25SGA*
IRR	0.964	0.977	0.979
IRR_N4		0.998	0.953
IRR_Q2			0.964

Panel C: Sector-Level *IRR*

Fiscal Year	Low-Tech			Stable-Tech			Health-High-Tech			Digital-High-Tech		
	IRR_Q2	*IRR_50RD _25SGA*	*IRR_N4*	*IRR_Q2*	*IRR_50RD _25SGA*	*IRR_N4*	*IRR_Q2*	*IRR_50RD _25SGA*	*IRR_N4*	*IRR_Q2*	*IRR_50RD_ 25SGA*	*IRR_N4*
1980	11%	7%	-4%	9%	7%	-7%	13%	9%	-2%	10%	7%	-5%
1981	11%	8%	-4%	9%	6%	-8%	13%	10%	-1%	12%	8%	-3%
1982	12%	8%	-4%	8%	5%	-9%	14%	10%	0%	13%	9%	-2%
1983	13%	9%	-2%	7%	5%	-10%	14%	11%	0%	13%	9%	-2%
1984	13%	9%	-1%	7%	5%	-10%	15%	12%	1%	12%	7%	-3%
1985	14%	10%	0%	8%	5%	-9%	16%	12%	3%	14%	10%	0%
1986	16%	11%	2%	6%	4%	-12%	18%	14%	6%	14%	10%	-1%
1987	14%	10%	0%	6%	3%	-12%	19%	14%	6%	12%	8%	-3%
1988	16%	11%	2%	10%	7%	-6%	20%	16%	9%	13%	10%	-1%
1989	14%	10%	0%	8%	5%	-9%	21%	16%	9%	13%	10%	-2%
1990	14%	10%	0%	7%	4%	-10%	21%	17%	10%	11%	9%	-4%
1991	13%	9%	-1%	5%	2%	-14%	22%	17%	11%	12%	9%	-3%
1992	15%	11%	0%	4%	2%	-15%	21%	17%	10%	11%	8%	-5%
1993	14%	11%	0%	5%	3%	-14%	21%	18%	10%	12%	9%	-4%
1994	15%	11%	1%	6%	4%	-12%	20%	17%	8%	13%	10%	-3%
1995	14%	10%	0%	6%	4%	-12%	20%	16%	7%	14%	10%	-2%
1996	14%	10%	-1%	7%	4%	-12%	19%	15%	6%	14%	11%	-1%
1997	14%	11%	0%	7%	5%	-11%	18%	15%	6%	15%	13%	1%
1998	16%	12%	3%	8%	6%	-9%	20%	16%	8%	17%	14%	3%
1999	15%	12%	2%	9%	6%	-9%	21%	17%	9%	19%	18%	9%

Table 10 continued

Fiscal Year	Low-Tech			Stable-Tech			Health-High-Tech			Digital-High-Tech		
	IRR_Q2	*IRR_50RD _25SGA*	*IRR_N4*	*IRR_Q2*	*IRR_50RD _25SGA*	*IRR_N4*	*IRR_Q2*	*IRR_50RD _25SGA*	*IRR_N4*	*IRR_Q2*	*IRR_50RD_ 25SGA*	*IRR_N4*
2000	14%	11%	0%	10%	5%	-10%	22%	18%	11%	20%	18%	9%
2001	14%	11%	0%	8%	5%	-11%	21%	18%	11%	14%	15%	5%
2002	13%	10%	-2%	7%	4%	-13%	20%	17%	9%	13%	14%	2%
2003	13%	10%	-1%	7%	5%	-12%	21%	18%	10%	15%	16%	4%
2004	14%	11%	-1%	8%	6%	-10%	23%	18%	11%	16%	16%	4%
2005	13%	10%	-2%	9%	6%	-9%	20%	16%	7%	16%	16%	4%
2006	13%	10%	-2%	11%	8%	-7%	20%	16%	7%	18%	17%	6%
2007	14%	10%	-1%	11%	8%	-7%	20%	16%	7%	17%	15%	4%
2008	12%	9%	-4%	10%	8%	-7%	19%	16%	6%	16%	16%	4%
2009	12%	9%	-3%	5%	3%	-15%	18%	15%	5%	16%	15%	2%
2010	13%	10%	-3%	8%	6%	-10%	18%	15%	4%	19%	19%	7%
2011	12%	10%	-3%	9%	7%	-9%	18%	16%	5%	18%	18%	6%
2012	13%	10%	-2%	6%	5%	-12%	17%	15%	4%	18%	18%	7%
2013	13%	10%	-2%	6%	5%	-13%	16%	14%	2%	18%	20%	10%
2014	12%	10%	-3%	5%	4%	-15%	18%	16%	4%	17%	18%	6%
2015	12%	10%	-3%	3%	2%	-17%	18%	16%	5%	16%	18%	6%
2016	11%	9%	-4%	2%	1%	-18%	17%	15%	3%	17%	19%	7%
2017	11%	8%	-6%	3%	2%	-18%	15%	14%	1%	17%	19%	7%
2018	12%	9%	-4%	4%	3%	-16%	17%	14%	2%	17%	20%	6%
2019	10%	8%	-6%	3%	3%	-17%	17%	15%	3%	18%	21%	9%