Rising Customer Durability, Falling Business Dynamism*

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ABSTRACT

We study how the durability of customer relationships shapes competition, innovation, and the allocation of economic activity. Using novel data from M&A accounting disclosures, we construct a forward-looking measure of customer durability based on firms' expected useful lives of their customer relationship-related intangible assets, covering nearly 9,500 acquisitions and $8 trillion in assets from 2002 through 2024. We document a substantial rise in durability across industries and examine its implications in an endogenous growth model in which longer-lasting customer relationships amplify incumbents' market power. Empirically, greater durability is associated with higher markups and profit shares, increased concentration, reduced entry and exit, lower job reallocation, slower wage growth, and a declining labor share. Consistent with our model, we also find an inverted-U relationship between durability and innovation, with high durability reducing both the quantity and quality of innovation, partly through lower R&D investment. Taken together, our findings highlight rising customer durability as a novel mechanism that helps reconcile the simultaneous increase in market power and decline in U.S. business dynamism, with important implications for competition policy.

JEL classifications: L11, L25, L41, O31, E25

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1. Introduction

Firms devote substantial investment to building and sustaining customer relationships (He et al., 2024), increasingly relying on data-rich management systems, subscription models (Einav et al., 2025), and loyalty programs that extend relationship horizons and "lock in" consumer demand (Farrell and Klemperer, 2007). These longer-lived relationships generate valuable intangible assets for firms, but they also influence competition by reducing the share of consumers who are contestable in any given period (Klemperer, 1987b; Beggs and Klemperer, 1992). As the pool of contestable customers contracts, entry incentives weaken (Klemperer, 1987a; Tirole, 1988), slowing the reallocation of demand across firms (Bronnenberg et al., 2012; Fishman and Rob, 2003; Gourio and Rudanko, 2014; Foster et al., 2016). Although this dynamic benefits incumbents, it potentially dampens the competitive forces that discipline market power and support productivity growth (Foster et al., 2008), firm turnover, and the broader processes of "creative destruction" (Schumpeter, 1942; Aghion and Howitt, 1992). Yet despite these far-reaching implications, we have limited empirical evidence on how long customer relationships actually persist, and even less on how long firms expect them to persist—the margin most relevant for pricing, investment, and strategic behavior.

To address this gap, we construct a novel, forward-looking measure of customer-relationship durability from firms' internal forecasts disclosed in mergers and acquisitions (M&A). These expectations—reflected in the useful-life assumptions attached to customer relationship-related intangible assets—provide a rare view into how long firms expect their relationships to last and allow us to ask: How do firms' expectations about relationship durability shape product-market competition and the reallocation of economic activity?

This question is not just of interest to economists. Regulators, industry analysts, and the business press have all noted that firms across many sectors are designing business models that extend customer relationships and reduce switching (e.g., Khan and Dayen, 2024; Zolman, 2025). Antitrust authorities now characterize loyalty programs, digital ecosystems, and subscription bundles as mechanisms that "lock in" consumers and insulate incumbents from competitive pressure—a concern that features prominently in recent actions by the Federal Trade Commission (FTC) and the Department of Justice (DOJ) (e.g., Federal Trade Commission, 2024; U.S. Department of Justice, 2024).[1] These views highlight a broader concern: firms' ability to cultivate and preserve long-lasting customer relationships is increasingly seen as a strategic source of market power with potentially important implications for competition and, ultimately, the dynamism of the U.S. economy.

We measure firms' expected durability of their customer relationships using M&A-related disclosures in the filings of U.S. public acquirers. These filings report, at the deal level, the specific types of intangible assets acquired in the transaction, their estimated fair values, and, in nearly all cases, the expected useful life assigned to each category of asset. These disclosures are particularly informative because the expected useful life of intangible assets is not systematically observable in any other setting. Our sample, which makes a novel data contribution, covers nearly 9,500 acquisitions involving customer relationship–related intangibles from 2002 to 2024, spanning all major industries and years.[2] In total, we find that acquirers reported more than $1 trillion in customer relationship–related intangible assets—over 20% of all identifiable assets recognized in these transactions—underscoring their economic importance.

We begin by documenting several key stylized facts in the data. First, as shown in Figure 1, the economy-wide mean useful life of customer relationships in the U.S. increased by more than 50 percent between 2002 and 2024, rising from 7.5 years to approximately 11.5 years. Second, Figure 2 shows that this upward trend in customer relationship durability is pervasive across the largest sectors of the economy, including manufacturing, information, professional services, financial services, and wholesale trade.

[1] Industry observers likewise highlight the rapid expansion of data-rich loyalty programs in retail and grocery, as well as the rise of tightly integrated software and device ecosystems in technology markets, as evidence that customer relationships are becoming more persistent and harder to dislodge. For instance, eMarketer (2024) reports that U.S. consumers held an average of 19 loyalty program memberships in 2024—the highest level in a decade; and these programs are increasingly drawing scrutiny for potential consumer harm (Consumer Reports, 2025).

[2] Our sample begins in 2002 because the Financial Accounting Standards Board (FASB) eliminated pooling-of-interests accounting with the issuance of SFAS 141 (effective for deals initiated after June 30, 2001). From that point forward, virtually all business combinations were required to be accounted for under the purchase method, which mandates the recognition and fair-value allocation of identifiable intangible assets—including customer relationships—through Purchase Price Allocations. Consistent application of the purchase method from 2001 onward ensures comparability in the measurement of acquired intangible assets and their expected useful lives.

To validate that our useful life estimates capture economically meaningful variation in the durability of customer relationships, we complement our durability measure with a textual analysis of acquiring firms' corporate disclosures. The intuition for this analysis is straightforward: because firms have incentives to communicate value-relevant drivers of future cash flows to investors, economically meaningful increases in customer durability should be reflected in their public disclosures. Consistent with this idea, we document a positive and statistically significant association between customer useful life estimates and post-acquisition changes in the share of keywords that either explicitly describe customer durability or capture mechanisms through which firms build and sustain customer relationships. Quantitatively, we find that a 1 percent increase in useful life is associated, on average, with a 0.6 percent increase in the share of these keywords.

While documenting the rise in customer durability is important, understanding how this shift reshapes product-market competition and the allocation of economic activity is equally vital, as it may help explain broader trends such as increasing market concentration and the slowdown in business dynamism in the U.S. economy. Motivated by this perspective, we develop an endogenous growth model of strategic competition and innovation in which customer durability amplifies the market power of leaders. Building on Akcigit and Ates (2023), we extend their step-by-step innovation framework by introducing a single parameter—the durability of customer relationships—that governs the extent to which incumbent leaders can price above the standard Bertrand limit. The model delivers empirical predictions for several outcomes that are consistent with recent changes in the U.S. business environment—rising markups (De Loecker et al., 2020), greater profit shares (De Loecker et al., 2020), increased market concentration (Gutiérrez and Philippon, 2017, 2016; Grullon et al., 2019; Barkai, 2020), declining entry (Gourio et al., 2014; Decker et al., 2016; Karahan et al., 2024), reduced job reallocation (Decker et al., 2014, 2016), and lower labor shares (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Autor et al., 2020; Barkai, 2020). We show that these patterns can arise from a unified mechanism—greater customer durability that shields market leaders from competitive pressure—which also helps explain why market leaders innovate less (Aghion et al., 2005; Gutiérrez and Philippon, 2017).

To assess these predictions empirically, we use the year in which the acquiring firm purchases customer relationship–related intangible assets as the event period, and examine the dynamic effects of the useful life of customer relationships on a range of firm-, industry-, and economy-level outcomes. The resulting empirical evidence is broadly consistent with the model's predictions. First, relative to the year prior to the acquisition, we find that a longer useful life of customer relationships is associated with higher gross profit margins in the post-acquisition period. One concern is that this increase could reflect a shift from variable to fixed costs due to greater reliance on customer-related intangible assets. To address this, we examine whether customer durability is also associated with changes in operating profit margins. If the results were driven purely by increased operating leverage, we would expect no change—or even a decline—in operating margins. Instead, we find that customer durability is associated with a positive and statistically significant expansion in operating profit margins following the acquisition. We also find that these higher operating margins then allow firms with more durable customer relationships to capture a larger share of industry profits.

A natural next question is whether similar inferences arise when using conventional measures of market structure, such as the Herfindahl–Hirschman Index (HHI). Although HHI is widely used in empirical work due to its observability, it is an imperfect proxy for market power, as changes in concentration can reflect factors unrelated to firms' ability to price above marginal cost (Syverson, 2019). Moreover, because HHI is a static measure of the distribution of market shares, it has long been criticized for providing limited insight into how competitive dynamics—and thus market power—evolve over time (Posner, 1976; Cohen and Sullivan, 1983). Consistent with these limitations, when we replace the useful life of customer relationships with HHI, measured in the acquisition year, we find no statistically significant relationship between HHI and subsequent changes in gross margins, operating profit margins, or the share of industry profits.

Second, a central implication of our model is that greater durability of customer relationships can increase market concentration through two distinct channels: a revenue channel and an entry channel. The revenue channel operates as follows. As leading firms raise prices above marginal cost while retaining their customer base, their revenues grow relative to those of their rivals, mechanically increasing revenue-based measures of market concentration. The entry channel operates through a reduction in competitive pressure. When customer durability is high, it can discourage the entry and expansion of followers and potential entrants, further concentrating market activity among market leaders. This prediction is consistent with a well-documented trend in the literature: a slowdown in new business formation in the United States, particularly among young, high-growth firms (Gourio et al., 2014; Karahan et al., 2024; Decker et al., 2016). Moreover, by limiting customer turnover and reducing the contestability of demand, greater durability also lowers firm exit, reinforcing concentration by slowing the reallocation of market share away from incumbents.

Our empirical results are consistent with these channels. We find that a longer useful life of customer relationships strongly predicts increases in HHI and declines in market entry and exit. By contrast, HHI itself is positively associated with future entry, implying that higher current concentration tends to erode over time as new firms enter and capture market share. Consistent with this pattern, we find that HHI is negatively related to future HHI.

A decline in entry in markets with fewer contestable customers has important implications for job reallocation. Young firms, in particular, play a central role in job creation and wage growth, facilitating the movement of workers from declining leaders to new innovators offering higher-paying opportunities. In our model, greater customer durability reduces market entry and concentrates labor demand among incumbent leaders. This mechanism suggests lower job reallocation, slower wage growth, and ultimately a decline in the labor share.

Consistent with these predictions, our empirical results show that the useful life of customer relationships is negatively and statistically significantly related to job reallocation rates, with effects that are persistent and increase monotonically in absolute value over time. We also find a negative and statistically significant relationship between customer durability and wage growth. Finally, we document that increases in customer durability are associated with a decline in the labor share, indicating that the benefits of long-lasting customer relationships are not shared with employees of these firms.

We next examine how customer durability shapes market leaders' incentives to innovate.

In the model, greater customer durability increases the value of leadership by allowing incumbents to preserve rents from an existing customer base. At low levels of durability, firms cannot appropriate the returns to innovation for long, resulting in weak incentives to innovate; as durability increases, leading firms have stronger incentives to invest in innovation to maintain their advantage and deter entry; however, at high levels of durability, competitive pressure from both followers and potential entrants declines, lowering the incremental benefit of innovating to preserve market leadership. The model therefore points to a non-monotonic effect of customer durability on leaders' incentives to innovate.[3]

Guided by this mechanism, we examine whether innovation outcomes vary non-monotonically with customer durability. Our empirical results indicate an inverted-U relationship between customer durability and both the share of patents granted in a given year and the share of forward citations, suggesting that longer-lasting customer relationships are associated with differences in both the quantity and quality of innovation produced by market leaders. Consistent with this pattern, we also find that firms with longer-lasting customer relationships produce innovations with more marginal contributions, as reflected in lower citations per innovator. Finally, we document that a key channel underlying these patterns is a decline in research and development (R&D) spending by firms with higher customer durability.

Our findings have important implications for competition policy. Much of the existing enforcement framework focuses on contemporaneous measures of market structure, such as concentration indices, to assess competitive harm. Our results suggest that these measures may miss a key, forward-looking dimension of market power: firms' ability to cultivate and sustain long-lasting customer relationships. When customer durability is high, competitive pressure from both entrants and rivals is reduced, even in markets that may not appear highly concentrated at a point in time. This highlights the importance of considering mechanisms such as switching costs, subscription models, loyalty programs, and ecosystem integration–not only as static features of markets, but as dynamic forces

[3]These predictions offer a potential explanation for several empirical patterns documented in the literature, including the declining relative innovative output and quality of mature firms (Akcigit and Goldschlag, 2023), the reduced frequency with which market leaders introduce new products (Argente et al., 2025), and the increasing tendency of leading firms to produce innovations with only marginal contributions (Akcigit and Goldschlag, 2023).

that shape entry, innovation, and the evolution of competition over time.

This article makes three main contributions to the literature. First, we provide micro-level evidence on the evolution of firms' estimated useful lives of their customer relationships, using comprehensive, economy-wide data. A growing literature studies how firms build and leverage these relationships (He et al., 2024; Hall, 2008; Gourio and Rudanko, 2014), given their implications for market power, churn, switching costs, loyalty, customer inertia, and the persistence of brand preferences (Morlacco and Zeke, 2021; Roldan-Blanco and Gilbukh, 2021; Baker et al., 2023; Dubé et al., 2009, 2010; Rudanko, 2017; Hortaçsu et al., 2017; MacKay and Remer, 2024; Bronnenberg et al., 2012; Bronnenberg and Dubé, 2017; Blumenfeld et al., 2026, among others). Our key distinction is that we directly observe how long firms expect these relationships to persist, yielding a forward-looking measure of customer durability that captures firms' ability to retain customers and shapes their incentives to invest, compete, and innovate. Moreover, the breadth of our data allows us to trace these patterns over long horizons and across industries—something not feasible in prior work—and to document a broad-based rise in customer relationship durability.

Second, we build on recent studies that seek to understand the common forces behind the joint rise in market power and the decline in U.S. business dynamism (Akcigit and Ates, 2023; Liu et al., 2022; Akcigit and Ates, 2021; Autor et al., 2020; De Loecker et al., 2020). In particular, Akcigit and Ates (2023) identifies declining knowledge diffusion as a central force behind these trends, while leaving open the question of what drives this decline. We propose that rising customer relationship durability is an important and previously overlooked mechanism that directly addresses this question. Although knowledge diffusion is not modeled explicitly, the framework points to a natural source of its decline: greater customer durability concentrates revenue and labor demand among incumbent leaders while reducing entry and reallocation, thereby limiting the movement of ideas across firms. Through this channel, the model helps account for rising markups and concentration alongside declines in entry, job reallocation, wage growth, and labor share.

Third, we contribute to the literature on competition and innovation (Aghion et al., 2005, 2001; Blundell et al., 1999). A central insight of this literature is that competitive pressure shapes firms' incentives to innovate: in step-by-step frameworks, firms invest to "escape competition," particularly when rivals are close (Aghion et al., 2001). Accordingly, in settings where incumbents face fewer threats from entry and rivals or can actively limit future competition, for example through acquisitions that eliminate competing innovation (Cunningham et al., 2021; Kepler et al., 2026; Kamepalli et al., 2022), weaker competitive pressure may reduce incentives to innovate. Consistent with this view, recent studies link declining competition to weaker investment and innovation (Gutiérrez and Philippon, 2017). We contribute by introducing customer relationship durability as a novel source of reduced competitive pressure. By limiting the pool of contestable customers, greater durability can dampen firms' incentives to innovate and generate an inverted-U relationship between durability and innovation, helping to explain the decline in both the quantity and quality of innovation among leading firms.

The remainder of the paper is organized as follows. Section 2 discusses the relevant institutional background, describes our data sources, and presents summary statistics. Section 3 documents key trends and validates our measure. Section 4 presents our theoretical framework. Section 5 tests implications for product-market competition, Section 6 examines economic reallocation, and Section 7 studies effects on innovation. Section 8 concludes.

2. Institutional Background and Data Sources

A central challenge in studying competition and business dynamism is that researchers rarely observe how long firms expect their customers to stay. This horizon—the expected duration of customer relationships—fundamentally shapes how much of a firm's demand is "contestable" in any period and therefore governs the strength of competitive pressure, the incentives for entry, and the scope for reallocation across firms. In this section we describe the institutional setting that generates our measure of relationship durability, discuss our data sources, and present summary statistics.

2.1 Useful life disclosures

When a firm acquires another business, U.S. Generally Accepted Accounting Principles (GAAP) require the acquirer to identify and measure at fair value all identifiable intangible assets, including customer-related intangibles such as customer lists, customer contracts, and customer relationships.[4] Under Accounting Standards Codifications (ASC) 805 and 350, the acquirer must also assign each identifiable intangible asset a useful economic life that reflects the period over which the asset is expected to contribute—directly or indirectly—to future cash flows. This requirement applies to both tangible and intangible assets, but it is particularly consequential for customer-related intangibles, whose economic value depends on the persistence of customer relationships over time.

Accounting standards emphasize that an asset's useful life is inherently entity-specific and must be determined using judgment based on all relevant facts and circumstances. ASC 350 outlines a non-exhaustive set of factors that guide this assessment, including the expected use of the asset by the firm; legal, regulatory, or contractual constraints; the firm's historical experience with renewals or extensions of similar arrangements; exposure to obsolescence, competition, and demand conditions; and the level of maintenance required to sustain future cash flows. Importantly, the assessment depends on the full set of factors rather than any one in isolation, and useful life is explicitly defined as the duration of expected economic benefits—not the time required to internally generate a similar asset.

For customer-related intangible assets, these general principles translate into a forward-looking assessment of customer retention and revenue durability. In practice, purchase price allocations are prepared primarily by independent third-party valuation specialists, working in conjunction with acquirer management, technical accounting consultants, and external auditors to comply with ASC 805. Using detailed internal customer relationship management data and historical purchasing patterns provided during due diligence, valuation specialists implement cohort-based retention models, attrition curves, renewal probabilities, and expected churn rates to estimate the expected persistence of customer relationships. The resulting useful-life estimate therefore represents a forecast of how long acquired customer relationships are expected to persist and generate cash flows,

[4] Under Accounting Standards Codification 805 (Business Combinations), the acquirer must recognize separately from goodwill all identifiable intangible assets acquired in a business combination and measure them at acquisition-date fair value. Identifiable intangible assets include those arising from contractual or legal rights or that are separable (ASC 805-20-20), and explicitly include customer-related intangibles such as customer lists, customer contracts, and customer relationships (ASC 805-20-55-20–55-27). More information on identifiable intangible assets can be found at https://asc.fasb.org/805-20/tableOfContent.

conditional on competitive dynamics, switching costs, and customer behavior.

Importantly, these estimates are subject to multiple layers of review. Valuation assumptions are scrutinized by external auditors and, particularly in large transactions, evaluated by boards of directors or audit committees. Because finite-lived customer assets must be amortized over their estimated useful economic lives, these assumptions have direct financial-statement consequences. Moreover, although useful-life estimation involves judgment, unsupported or biased valuation assumptions can give rise to regulatory scrutiny, accounting restatements, and enforcement actions, providing additional discipline. Taken together, reported useful lives embed the acquirer's internal assessments of customer retention, switching behavior, and the longevity of revenue streams—information that is rarely observable outside the acquisition setting. Nonetheless, we assess the reliability of these estimates by conducting a series of validation tests in subsequent sections.

2.2 Primary data sources

We hand-collect the reported fair values of all tangible assets, identifiable intangible assets, goodwill, and assumed liabilities acquired in mergers and acquisitions undertaken by U.S. publicly listed firms from 2002 to 2024.[5] These data are obtained from Purchase Price Allocations (PPAs) disclosed in firms' annual U.S. Securities and Exchange Commission (SEC) Form 10-K filings; Online Appendix A, Panel B presents a representative PPA disclosure. For transactions reporting identifiable intangible assets, we additionally collect acquirers' disclosed estimates of asset useful lives, with a sample disclosure shown in Online Appendix A, Panel C. The resulting dataset comprises nearly 21,000 acquisitions, totaling approximately $15.5 trillion in acquired assets. From this universe, we focus on nearly 9,500 transactions that report customer relationship–related intangible assets and their useful economic lives, representing $8 trillion in assets (52% of the sample), including just over $1 trillion in customer-related intangibles.[6]

[5]Online Appendix A describes the sample restrictions.

[6]We exclude 636 acquisitions by banks, as their customer-related intangible assets primarily take the form of core deposit intangibles (CDIs).

2.3 Other data sources

Data for our main outcome variables are obtained from several sources. We obtain firm-level accounting data used to describe acquirers and to analyze gross margins, operating profit margins, and R&D expenditures from Compustat. We measure industry concentration (Herfindahl-Hirschman Index) at the six-digit NAICS level using publicly available data obtained from the U.S. Census Bureau's Economic Census. The primary advantage of using U.S. Census HHI ratios is that it provides comprehensive, establishment-level coverage of the entire population of firms within narrowly defined industries, allowing concentration to be measured without the sampling error, reporting bias, or truncation issues that often affect commercially available datasets.

For our main analysis of job reallocation rates, we rely on employee headcount data from Compustat, consistent with our acquirer-level financial information, which is drawn from the same source. In additional analyses, we incorporate data from Revelio Labs, enabling us to examine both job reallocation rates and wage changes.[7] As a further robustness check, we use the U.S. Census Bureau's Business Dynamics Statistics (BDS) to validate our findings on job reallocation rates. The BDS is also our source for data to conduct tests of firm entry rates and the employment share of young firms.

We use the repository of patent data constructed and shared publicly by Kogan et al. (2017) for our innovation-related tests. Finally, tests of firms' textual disclosures are conducted using data obtained from the public repository of parsed SEC filings shared publicly by Codesso et al. (2025) at Analytext.com.

2.4 Summary statistics

Table 1, Panel A reports summary statistics for our sample of 9,444 acquisitions. The average acquirer holds $7.9 billion in total assets, and the mean purchase price is slightly above $500 million. On average, firms allocate $112 million of the purchase price to customer relationship–related intangible assets, representing approximately 22% of deal value. Relative to the acquirer's balance sheet, these assets amount to 2.6% of total assets.

[7] Revelio Labs data are a private, worker-level panel dataset constructed from online résumés and job postings that track individuals' employment histories, skills, and employer transitions, allowing researchers to study labor flows, firm workforce composition, and organizational dynamics in near real time.

The average reported useful life of customer relationship intangibles is 10 years. Notably, the 90-10 percentile difference is 13 years (17 vs. 4), and the 75-25 percentile difference is 7.2 years (13.2 vs. 6), indicating substantial dispersion.

To further examine the dispersion of useful life estimates, Panel B aggregates observations into non-overlapping two-year periods. The cross-sectional dispersion, measured by the standard deviation, remains remarkably stable over time, ranging from 4.59 to 5.67. In columns 3 to 5 we analyze within-acquirer variation by restricting the sample to 5,334 observations in which an acquirer completed more than one transaction within a two-year period. This approach allows us to assess the economic content of the estimates: meaningful variation in useful lives assigned by the same acquirer suggests that these figures are not merely rule-of-thumb conventions. Consistent with this interpretation, we document substantial within-acquirer dispersion, averaging between 1.58 and 2.00 over the sample period. Economically, this implies that more than 30% of the variation in useful life estimates within a given two-year period arises from the same firm assigning different useful lives to customer relationship–related intangibles across transactions.

3. Durability of Customer Relationships

Figure 1 plots the average useful life of customer relationships over time. The figure reveals a pronounced upward trend: between 2002 and 2024, the average useful life rises by about 50 percent, from roughly 7.7 to 11.5 years. In this section, we explore the industries driving this trend, and validate the economic content of our measure.

3.1 Industry trends and distributions

3.1.1. Trends

As shown in Panel C of Table 1, the nine largest industries in our sample account for 87% of all observations. Figure 2 plots the evolution of useful life estimates within each of these industries and reveals that the upward trend is broad-based and evident across nearly all of them. In Online Appendix D, we disaggregate the six largest two-digit industries into their three-digit NAICS subsectors and rank them by sample share. We focus on the top six subsectors—together accounting for just over 40% of our full sample—and plot the evolution of their useful life estimates in Panel B of Figure 2.

Upwards trends are evident across all major subsectors. In computer and electronic product manufacturing (NAICS 334), the largest subsector in our data, the average useful life rises from roughly 7 years to more than 12 years—an increase of nearly 75%. Comparable or even larger increases appear in professional, scientific, and technical services (NAICS 541); cloud, data processing, and web hosting (NAICS 518); and software publishers (NAICS 5132). In chemical manufacturing (NAICS 325), which includes pharmaceutical firms, the increase in customer-relationship durability is more modest but still substantial, rising from approximately 11 years to about 14 years, or roughly 27%.

Overall, the consistency of these increases across industries and subsectors suggests that the upward trend in customer-relationship durability reflects a pervasive shift in the economy rather than industry-specific dynamics.

3.1.2. Distributions

We next examine the cross-sectional distribution of durability estimates. Figure 3 presents a histogram with one-year bins for the full sample. The distribution is centered around a mean of 10 years and is approximately symmetric. At the same time, we observe pronounced spikes at 5, 10, 15, and 20 years, suggesting that some estimates may reflect rule-of-thumb assumptions, industry or firm conventions, or mechanical rounding. The modal bin—covering useful lives between 10 and 11 years—accounts for approximately 13% of observations.

Table 1, Panel C reports summary statistics by two-digit NAICS industry. Focusing on the top nine industries, we document substantial within-industry dispersion. In manufacturing (NAICS 33), the interquartile range spans from 6 to 14.5 years, while the 10th–90th percentile range extends from 4.6 to 18 years. These wide spreads are mirrored in the standard deviations, which range from 4.18 in information (NAICS 51) to nearly 7 in real estate (NAICS 53). Figure 3, Panel B visualizes these distributions for the top nine industries. Consistent with the full sample, the within-industry distributions are generally symmetric around their respective means.

3.2 Validating the measure

To validate that our useful life estimates capture economically meaningful variation in the durability of customer relationships, we complement the useful life data with a textual analysis of acquiring firms' corporate disclosures found in Items 1 (business description) and 7 (management discussion and analysis) of their Form 10-K annual filings.[8] Because firms have incentives to communicate value-relevant drivers of future cash flows to investors, economically meaningful increases in customer-relationship durability should be reflected in greater textual emphasis on customer retention, repeat purchasing, and related mechanisms in 10-K disclosures.

For this analysis, we measure changes in the frequency of keywords mentioned in these disclosures before and after the acquisition of customer relationship-related intangible capital. Our keyword list comprises words or combinations of words that are indicators of the importance of customer relationships to firms—such as language explicitly describing durability, repeat purchasing behavior, and low churn. However, we also include keywords that capture mechanisms by which firms build and sustain customer relationships, such as subscription models, loyalty programs, and network benefits. A complete list of the keywords we analyze is shown in Online Appendix E.

We construct our keyword measure at the firm-year level for each acquirer in our sample. For each year, beginning in the year prior to the M&A deal (t-1) and ending three years after the acquisition year (t+3), we count the occurrences of our key words within Items 1 and 7, collectively, and then scale this count by the total number of words in these two items. Next, we compute the logged difference between years t-1 and t+n. Figure 4 presents binscatter plots of the logged difference of t-1 and t+3 on the y-axis, $\Delta Allwords$, and the natural logarithm of useful life estimates on the x-axis. The slope coefficient from a log-linear regression that includes industry and year fixed effects is 0.59 and statistically significant at the 5 percent level, implying that a 1 percent increase in useful life is associated, on average, with a 0.59 percent increase in the share of keywords.

4. Theoretical Framework

To guide the empirical analysis, we embed customer durability into an endogenous growth model with step-by-step innovation a la Akcigit and Ates (2023). Specifically, we introduce a reduced-form parameter, $\phi \in [0, 1)$, that captures the durability of customer

[8] A vast literature has leveraged the textual disclosures in firms' Form 10-K filings to study a wide range of questions in accounting, finance, and economics.

relationships. Higher customer durability allows incumbent leaders to preserve rents from an existing customer base. In this framework, we examine the implications of increasing customer durability on pricing, profitability, innovation incentives, and equilibrium market structure.[9]

4.1 Environment

Time is continuous. A representative household supplies labor inelastically and consumes the final good. Along a balanced growth path, consumption grows at a constant rate g, and the interest rate satisfies $r = \rho + g$, where $\rho > 0$ is the rate of time preference.

A competitive final-good producer combines a continuum of intermediate varieties, indexed by $j \in [0, 1]$, according to

$$\ln Y_t = \int_0^1 \ln y_{jt} \, dj, \tag{1}$$

which implies unit-elastic demand for each intermediate good:

$$y_{jt} = \frac{Y_t}{p_{jt}}. \tag{2}$$

In each product line j, two incumbent firms indexed by $i \in \{1, 2\}$ can produce the intermediate good using labor according to

$$y_{ijt} = q_{ijt} \ell_{ijt}, \tag{3}$$

so marginal cost of production is $mc_{ijt} = w_t / q_{ijt}$. Productivity evolves on a quality ladder: after n successful innovations, a firm's productivity is $q = \lambda^n$, where $\lambda > 1$ is the innovation step size.

As in Akcigit and Ates (2023), the state of a product line is summarized by the technology gap between the two incumbents. Let $m \in \{0, 1, \ldots, \bar{m}\}$ denote the number of steps by which the leader is ahead of the follower. When $m = 0$, the sector is neck-and-neck; when $m > 0$, the sector is unleveled.

4.2 Customer durability and pricing

The key departure from the Akcigit and Ates (2023) framework is that we allow for customer durability, which enables the leader to price above the standard limit price. We model this in reduced form by introducing a parameter $\phi \in [0, 1)$ that governs the degree

[9]Our analysis here focuses on analytical comparative statics.

of customer durability. When $\phi = 0$, the model reduces to the standard Bertrand pricing outcome. When $\phi > 0$, incumbent leaders can sustain prices above the follower's marginal cost without losing their customer base.

Consider an unleveled sector with gap $m > 0$. Under standard Bertrand competition, the leader prices at the follower's marginal cost. With customer durability, the leader can instead charge

$$p_L = \frac{mc_F}{1-\phi} = \frac{w}{q_F(1-\phi)}. \tag{4}$$

Since $q_L = \lambda^m q_F$, the leader's markup is

$$\kappa(m,\phi) = \frac{p_L}{mc_L} = \frac{\lambda^m}{1-\phi}. \tag{5}$$

Normalizing by aggregate output, the leader's flow profit in an unleveled sector is

$$\pi_m \equiv \frac{\pi(m,\phi)}{Y} = 1 - (1-\phi)\lambda^{-m}, \qquad m > 0. \tag{6}$$

In neck-and-neck sectors, each incumbent serves half the market and earns

$$\pi_0 \equiv \frac{\pi(0,\phi)}{Y} = \frac{\phi}{2}. \tag{7}$$

A central implication is that customer durability raises the level of profits at every state while reducing the incremental gain from widening a lead:

$$\Delta\pi(m,\phi) \equiv \pi_{m+1} - \pi_m = (1-\phi)\lambda^{-m}(1-\lambda^{-1}). \tag{8}$$

This wedge is the core force shaping innovation incentives below.

4.3 Innovation and firm values

Incumbents invest in R&D to improve their productivity. Let x_m denote the leader's innovation rate in an unleveled sector with gap m, x_{-m} the follower's innovation rate, and $\tilde{x}_{-m}$ the entrant's innovation rate. Incumbent R&D is conducted using labor, and the cost of achieving innovation rate x is $\frac{\alpha x^\gamma}{\gamma} w$, where $\alpha > 0$ is a scale parameter and $\gamma > 1$ governs diminishing returns to R&D effort. Entrants face an analogous technology with cost $\frac{\tilde{\alpha}\tilde{x}^{\tilde{\gamma}}}{\tilde{\gamma}} w$, where $\tilde{\alpha} > 0$ and $\tilde{\gamma} > 1$ are entrant-specific parameters.

When a leader innovates, its productivity increases by factor λ, and the technology gap widens by one step. When a follower innovates, with probability $(1-\delta)$, the innovation is incremental: the follower's productivity increases by factor λ, narrowing the gap by one step. With probability δ, the innovation is drastic: the follower catches up fully to the leader's productivity level. Entrants' innovation is defined similarly with a drastic innovation probability of $\tilde{\delta}$. Let v_m denote the value of a firm that is m steps ahead of its rival, normalized by aggregate output. For a leader with gap $m > 0$,

$$\rho v_m = \max_{x_m} \left\{ \pi_m - \frac{\alpha x_m^{\gamma}}{\gamma}\omega + x_m(v_{m+1} - v_m) + \Phi_{-m}(v_{m-1} - v_m) + \Psi_{-m}(v_0 - v_m) \right\}, \tag{9}$$

where $\omega \equiv w/Y$, $\Phi_{-m} \equiv (1-\delta)x_{-m} + (1-\tilde{\delta})\tilde{x}_{-m}$ is the rate of incremental catch-up, and $\Psi_{-m} \equiv \delta x_{-m} + \tilde{\delta}\tilde{x}_{-m}$ is the rate of drastic catch-up.

The follower and neck-and-neck value functions are defined analogously. Optimal innovation rates satisfy[10]

$$x_m = \left[\frac{v_{m+1} - v_m}{\alpha\omega}\right]^{1/(\gamma-1)}, \qquad x_{-m} = \left[\frac{(1-\delta)(v_{-(m-1)} - v_{-m}) + \delta(v_0 - v_{-m})}{\alpha\omega}\right]^{1/(\gamma-1)}, \tag{10}$$

and

$$x_0 = \left[\frac{v_1 - v_0}{\alpha\omega}\right]^{1/(\gamma-1)}. \tag{11}$$

Labor-market clearing requires production labor and R&D labor to sum to one. This implies

$$\omega = \frac{(1-\phi)\left[\mu_0 + \sum_{m=1}^{\bar{m}} \mu_m \lambda^{-m}\right]}{1 - L^{R\&D}}, \tag{12}$$

where $L^{R\&D}$ denotes aggregate labor used in incumbent and entrant R&D. Finally, let μ_m denote the stationary share of product lines with gap m. Aggregate productivity growth is then

$$g = \ln\lambda \left[2\mu_0 x_0 + \mu_0\tilde{x}_0 + \sum_{m=1}^{\bar{m}} \mu_m x_m\right]. \tag{13}$$

A balanced growth path equilibrium consists of values, innovation rates, wages, and a stationary distribution of technology gaps such that firms optimize, entrants optimize, the labor market clears, and the distribution of sectors evolves consistently with innovation and entry.

4.4 Comparative Statics

An increase in ϕ corresponds to greater durability of customer relationships. In the model, higher customer durability affects firm behavior through two distinct margins.

[10] Entrant policy rules are reported in Online Appendix C.

First, it raises the rents that can be extracted from an existing customer base. Second, it changes the value of widening, preserving, or overturning a technology lead. Some implications follow directly from the pricing block and hold within any given state. Other implications depend on how customer durability changes innovation rates and the stationary distribution of technology gaps.

Profitability. Consider first an unleveled sector with gap $m > 0$. The leader's markup is

$$\kappa(m, \phi) = \frac{\lambda^m}{1 - \phi}, \tag{14}$$

and the leader's normalized operating profit is

$$\pi_m \equiv \frac{\pi(m, \phi)}{Y} = 1 - (1 - \phi)\lambda^{-m}. \tag{15}$$

In a neck-and-neck sector, each incumbent earns

$$\pi_0 \equiv \frac{\pi(0, \phi)}{Y} = \frac{\phi}{2}. \tag{16}$$

These expressions imply

$$\frac{\partial \kappa(m, \phi)}{\partial \phi} = \frac{\lambda^m}{(1 - \phi)^2} > 0, \qquad \frac{\partial \pi_m}{\partial \phi} = \lambda^{-m} > 0, \qquad \frac{\partial \pi_0}{\partial \phi} = \frac{1}{2} > 0. \tag{17}$$

Thus higher customer durability mechanically raises markups and operating profits in every market structure state.

At the same time, customer durability compresses the incremental gain from widening a lead. The flow-profit gain from moving from gap m to $m + 1$ is

$$\Delta \pi_m \equiv \pi_{m+1} - \pi_m = (1 - \phi)\lambda^{-m}(1 - \lambda^{-1}), \tag{18}$$

so

$$\frac{\partial \Delta \pi_m}{\partial \phi} = -\lambda^{-m}(1 - \lambda^{-1}) < 0. \tag{19}$$

Hence customer durability raises the level of profits while reducing the marginal return to widening the technology gap.

A related object is the gain from escaping neck-and-neck competition:

$$\pi_1 - \pi_0 = 1 - (1 - \phi)\lambda^{-1} - \frac{\phi}{2}. \tag{20}$$

Its derivative is

$$\frac{d(\pi_1 - \pi_0)}{d\phi} = \lambda^{-1} - \frac{1}{2}. \tag{21}$$

Accordingly, whenever the innovation step size is sufficiently small ($\lambda < 2$), the direct flow-profit gain from moving from $m = 0$ to $m = 1$ is increasing in customer durability.

Market structure. The model's natural analogue of concentration is the prevalence of exclusive leadership states. Let $H(m)$ denote within-line HHI over revenue shares. Then

$$H(0) = \left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^2 = \frac{1}{2}, \qquad H(m) = 1 \quad \text{for all } m > 0. \tag{22}$$

Average concentration is therefore

$$\bar{H} = \frac{1}{2}\mu_0 + \sum_{m=1}^{\bar{m}} \mu_m = 1 - \frac{1}{2}\mu_0. \tag{23}$$

It follows immediately that

$$\frac{d\bar{H}}{d\phi} > 0 \iff \frac{d\mu_0}{d\phi} < 0. \tag{24}$$

Thus customer durability increases concentration if and only if it reduces the stationary share of neck-and-neck sectors.

Employment concentration and labor-market dynamism. The model implies that higher customer durability can make employment more concentrated in dominant firms. At the operating level, all production labor in an unleveled sector is employed by the leader, whereas production labor is split across active firms in a neck-and-neck sector. Leader production employment is therefore

$$L^{prod,L}(\phi) = \sum_{m=1}^{\bar{m}} \mu_m \frac{1-\phi}{\omega\lambda^m}, \tag{25}$$

while neck-and-neck production employment is

$$L^{prod,C}(\phi) = \mu_0 \frac{1-\phi}{\omega}. \tag{26}$$

The leader share of production employment is

$$s^{prod,L}(\phi) = \frac{L^{prod,L}}{L^{prod,L} + L^{prod,C}} = \frac{\sum_{m=1}^{\bar{m}} \mu_m \lambda^{-m}}{\mu_0 + \sum_{m=1}^{\bar{m}} \mu_m \lambda^{-m}}. \tag{27}$$

Accordingly, customer durability shifts operating employment toward dominant firms whenever it reduces the prevalence of neck-and-neck competition.

For R&D labor, the employment by the leaders and non-leaders are, respectively,

$$L^{R\&D,L} = \sum_{m=1}^{\bar{m}} \mu_m \frac{\alpha}{\gamma} x_m^{\gamma}, \qquad L^{R\&D,N} = \mu_0 \left[2\frac{\alpha}{\gamma} x_0^{\gamma} + \frac{\tilde{\alpha}}{\tilde{\gamma}} \tilde{x}_0^{\tilde{\gamma}} \right] + \sum_{m=1}^{\bar{m}} \mu_m \left[\frac{\alpha}{\gamma} x_{-m}^{\gamma} + \frac{\tilde{\alpha}}{\tilde{\gamma}} \tilde{x}_{-m}^{\tilde{\gamma}} \right]. \tag{28}$$

Higher customer durability lowers challenger-oriented knowledge labor whenever it sufficiently reduces follower and entrant innovation.

Entry. Customer durability affects entry through both expected returns and equilibrium labor costs. In an unleveled sector, the entry rate is:

$$\tilde{x}_{-m} = \left[\frac{(1-\tilde{\delta})v_{-(m-1)} + \tilde{\delta} v_0}{\tilde{\alpha}\omega} \right]^{\frac{1}{\tilde{\gamma}-1}}. \tag{29}$$

Accordingly, entry falls with customer durability whenever the decline in the value of entering against an entrenched leader dominates any offsetting reduction in wage costs.

Labor share and wages. The normalized wage, which also corresponds to the labor share in this environment, satisfies

$$\omega = \frac{(1-\phi)A(\mu)}{1-L^{R\&D}}, \qquad A(\mu) \equiv \mu_0 + \sum_{m=1}^{\bar{m}} \mu_m \lambda^{-m}. \tag{30}$$

Differentiating yields

$$\frac{d\ln\omega}{d\phi} = -\frac{1}{1-\phi} + \frac{d\ln A(\mu)}{d\phi} + \frac{1}{1-L^{R\&D}}\frac{dL^{R\&D}}{d\phi}. \tag{31}$$

The first term is mechanically negative. The second term is also non-positive if higher customer durability shifts activity toward larger technology gaps. The third term captures the offsetting role of R&D labor demand. Hence customer durability lowers the labor share whenever its direct effect on production labor demand, together with any shift toward more leader-dominated sectors, is not offset by a sufficiently large increase in R&D labor demand.

For production labor, in an unleveled sector with gap $m > 0$, the leader's production labor is $\ell_L(m) = (1-\phi)Y/(\omega\lambda^m)$, so the corresponding labor share is

$$LS^{prod}(m,\phi) \equiv \frac{w\ell_L(m)}{Y} = (1-\phi)\lambda^{-m}. \tag{32}$$

In a neck-and-neck sector, total production labor is $(1-\phi)/\omega$, implying

$$LS^{prod}(0,\phi) = 1-\phi. \tag{33}$$

Thus higher customer durability lowers the production labor share within every market-structure state. At the aggregate level, this direct effect can be reinforced if customer durability shifts activity toward larger technology gaps and weakens follower and entrant labor demand.

Innovation. Innovation incentives depend on how customer durability changes both the payoff to leadership and the payoff to catching up. Leader innovation at gap m is given by

$$x_m = \left[\frac{v_{m+1} - v_m}{\alpha\omega}\right]^{\frac{1}{\gamma-1}}. \tag{34}$$

Customer durability affects x_m through two opposing forces. On the one hand, greater durability tends to protect leadership by reducing the intensity of follower and entrant challenges, which raises the expected duration of a leadership position. On the other hand, greater durability lowers the incremental flow-profit gain from widening a lead, since $\Delta\pi_m$ is scaled by $(1-\phi)$. As a result, leader innovation need not be monotone in ϕ: when customer durability is initially low, the protection effect can dominate and leader innovation can rise; when customer durability is sufficiently high, marginal-return compression can dominate and leader innovation can fall.

Finally, aggregate growth is

$$g = \ln\lambda \left[2\mu_0 x_0 + \mu_0 \tilde{x}_0 + \sum_{m=1}^{\bar{m}} \mu_m x_m\right]. \tag{35}$$

Customer durability therefore affects growth through both the intensive margin (innovation rates within each state) and the composition margin (the distribution of sectors across states). If greater customer durability shifts the economy away from neck-and-neck sectors and sufficiently compresses innovation by leaders, aggregate innovation and growth decline. If the protection effect dominates at low values of ϕ, innovation may instead rise initially before declining at higher values of durability. This mechanism generates an inverted-U relationship between customer durability and innovation.

4.5 Empirical Predictions

The comparative statics yield a set of predictions that guide the empirical analysis. Some are monotone and follow directly from the pricing block. Others are equilibrium predictions that depend on how customer durability changes innovation incentives and the stationary distribution of technology gaps.

Prediction 1: Customer durability raises profitability. The clearest prediction concerns profitability. Because higher customer durability allows firms to sustain higher prices relative to marginal cost, firms with more durable customer relationships should exhibit larger post-acquisition increases in gross profit margins. Since the model also predicts that operating profits rise with customer durability, these firms should also experience larger increases in operating profit margins. Moreover, because customer durability both raises leader profits within a given state and makes leadership positions more persistent, firms with more durable customer relationships should capture a larger share of total industry profits.

The profitability effects should also be persistent. To the extent that customer durability makes leadership positions more durable and slows the erosion of incumbent rents, the profitability gains associated with durable customer relationships should become more visible over longer post-acquisition horizons. This prediction maps directly to our tests using changes in gross margins, operating margins, and firms' shares of industry profits.

Prediction 2: Customer durability increases concentration and weakens business dynamism. The model predicts that customer durability can increase market concentration by reducing the prevalence of neck-and-neck competition and making leadership positions more persistent. Accordingly, industries with more durable customer relationships should experience subsequent increases in concentration.

The same mechanism weakens business dynamism. Customer durability lowers the value of entering against a more protected incumbent and can reduce both establishment entry and firm entry. In the labor market, the direct implication of the model is that employment shifts away from followers and entrants and toward leaders. Because followers and entrants are the margins along which industries generate a disproportionate share of job creation and job destruction, this employment shift should also appear empirically as lower rates of cross-firm job reallocation and, where observable, lower employment shares for smaller or younger firms.

Customer durability should also depress labor's share of output. By allowing incumbents to extract a larger share of revenue as rents and by shifting activity toward more leader-dominated sectors, greater durability lowers the share of output paid to labor unless offset by a sufficiently strong increase in R&D labor demand. On a balanced growth path, slower innovation-driven growth also implies slower wage growth. These predictions map directly to our tests using changes in HHI, entry rates, job reallocation, wage growth, and labor share.

Prediction 3: Customer durability has non-monotone effects on innovation. Unlike profitability, the innovation effects of customer durability need not be monotone. At low levels of durability, firms may be unable to preserve the gains from innovation for long enough to justify substantial innovative effort. In that region, a rise in customer durability can strengthen innovation by protecting the returns to leadership. At higher levels of durability, however, the marginal return to widening the technology gap is compressed and the threats posed by followers and entrants become weaker. In that region, customer durability reduces the incentive to continue innovating.

This mechanism implies that innovation can be inverted-U in customer durability. For firms with more durable customer relationships, the share of industry innovation—measured either by patent counts or by forward citations—may initially rise and then fall as durability becomes sufficiently high. The same logic applies to measures of innovation quality. When customer durability becomes very high, leaders remain protected even while producing innovations of lower marginal value, implying weaker forward-citation performance and lower citations per innovator. This prediction motivates our nonlinear specifications for firms' shares of patents and citations, as well as our tests based on forward citations per innovator.

5. Durability and Profitability

We begin by examining the first prediction of our theoretical framework, namely, that greater durability of customer relationships allows firms to price above the competitive limit price.[11] The underlying intuition is that longer durability reflects the presence of customer frictions—such as switching costs, search costs, habit formation, or contractual lock-in—that reduce customers' sensitivity to price differentials and enable firms to sustain

[11] In the standard model, the limit price equals the follower's marginal cost.

higher markups. To test this implication, we analyze post-acquisition changes in gross profit margins, operating profit margins, and firms' share of industry profits, measured relative to the pre-acquisition period. To capture the model's implication of profit persistence, we then trace the dynamic evolution of these effects by progressively expanding the post-acquisition window in subsequent specifications. Specifically, we estimate the following regression model:

$$\begin{aligned}\Delta y_{i,j,t-1,t+n} = \beta_1\, ln(\mathit{UsefulLife})_{i,j,t} \times \mathit{Weight}_{i,j,t} + \beta_2\, ln(\mathit{UsefulLife})_{i,j,t} \\ + \beta_3\, \mathit{Weight}_{i,j,t} + \gamma_j + \tau_t + \epsilon_{i,t}\end{aligned} \tag{36}$$

where our dependent variable, $\Delta y_{i,t-1,t+n} \equiv y_{i,t+n} - y_{i,t-1}$, denotes the log difference in gross profit margin, operating profit margin, or industry profit share between $t-1$ and $t+n$, for firm i in industry j. Our measure of customer durability, $ln(UsefulLife)$, is the natural logarithm of the useful life of customer relationship-related intangibles acquired at time t by firm i in industry j. We use the logarithmic transformation because the distribution of useful lives is right-skewed, as shown in Figure 3. When firms make multiple acquisitions of customer relationship–related intangibles in a given year, we compute a value-weighted useful life, weighting each useful life estimate by the value of the acquired intangible relative to the total value of such intangibles acquired that year.

To capture the economic importance of the acquired intangible asset to the acquirer, we include the variable $Weight$, defined as the value of customer relationship–related intangibles acquired scaled by the acquirer's total assets, both measured at time t. The intuition is that longer customer-relationship useful lives should have larger effects on firm-level profit margins when the associated intangible asset represents a greater share of the firm's asset base. Accordingly, we interact $\ln(UsefulLife)$ with $Weight$. Variable descriptions and data sources are provided in Appendix A. Finally, we include industry fixed effects (γ) to account for time-invariant heterogeneity and year fixed effects (τ) to account for differences across time. Standard errors are clustered at the industry level.

5.1 Gross profit margins

Figure 5 presents motivating evidence by plotting the 90th percentile of industry-level gross margins—computed using firm revenue shares as weights—over time (red line), alongside the industry-level average durability of customer relationships (blue dotted line).

The two series exhibit strikingly similar trends across industries.

We next turn to a regression analysis. Specifically, we estimate Equation 36 to examine whether longer customer relationship durability is associated with increases in firms' gross margins—our accounting-based proxy for markups.[12] We begin by measuring the log difference in gross margins between $t-1$ and $t+1$, where t is the acquisition year, and then progressively extend the horizon to $t+2$ and $t+3$. Panel A of Table 2 reports the results.

The coefficient on the interaction between $ln(UsefulLife)$ and $Weight$ is our primary coefficient of interest. In columns (1) to (3), which include industry fixed effects, we find a positive and statistically significant relationship at the 5 percent level between the interaction term and changes in gross margins. This result indicates that longer-lived customer relationships that are economically more important to the firm are associated with increases in gross profit margins, and that this relationship persists over time. In columns (4) to (6), the results remain similar when year fixed effects are also included in the specification.

A natural next question is whether similar inferences arise when competition is measured using conventional industry concentration metrics. To examine this, we re-estimate Equation 36 replacing $ln(UsefulLife)$ with the natural logarithm of the Herfindahl–Hirschman Index ($ln(HHI)$), a commonly used proxy for market concentration. While concentration measures such as HHI are frequently used in empirical work due to their observability, they are only imperfect proxies for market power, since changes in concentration can arise from factors unrelated to firms' ability to price above marginal cost (Syverson, 2019). Moreover, HHI captures the current distribution of market shares but provides limited information about how competitive dynamics—and therefore market power—may evolve over time. Estimating the model with $ln(HHI)$ therefore provides a useful benchmark for assessing whether the durability of customer relationships captures competitive forces that are not reflected in standard concentration-based measures. We present the results of this analysis in Panel B.

In column (1), the interaction term is positive and statistically significant at the 10

[12] We use gross margins as a proxy for markups, given well-known concerns with production function–based approaches when only revenue data—rather than separate information on prices and quantities—are available, as is the case in our setting (Bond et al., 2021).

percent level. However, in column (2) the coefficient becomes statistically insignificant, and in column (3) it turns negative and remains insignificant. Columns (4) through (6), which additionally include year fixed effects, yield similar results. Overall, the evidence in Panel B suggests that current-period HHI provides limited information about future changes in market power.

5.2 Operating profit margins

In our next set of tests, we examine whether the relationship between longer customer-relationship durability and firms' profit margins also extends to operating margins. This analysis allows us to assess whether the widening of gross margins simply reflects a change in operating leverage—that is, firms shifting costs from variable to fixed components. If this were the case, gross margins would widen while operating margins would remain unchanged or potentially decline. Our theoretical framework predicts that operating profits are increasing in the durability of customer relationships. Figure 6 provides suggestive evidence by plotting the 90th percentile of industry-level operating margins–computed using firm revenue shares as weights—over time (red line), together with the industry-level average durability of customer relationships (blue dotted line). Across all industries, we find that

To test this more formally, we estimate Equation 36 using $\Delta EbitMargin$ as the dependent variable, defined as the log change in firms' operating margins between $t-1$ and $t+n$, where t denotes the acquisition year. We report results of this test in Panel A of Table 3. In columns (1) to (3), we generally find that longer durability of customer relationships is associated with increases in firms' operating margins. In column (1), which measures the change between $t-1$ and $t+1$, the estimated coefficient on the interaction between $ln(UsefulLife)$ and $Weight$ is positive but not statistically significant. However, when we expand the window to $t+2$ and $t+3$ in columns (2) and (3), respectively, the relationship becomes statistically significant, and the magnitude of the coefficient increases. This pattern suggests that the profitability effects of longer-lasting customer relationships materialize gradually over time, consistent with the idea that the economic benefits of these relationships are realized as firms integrate the acquired customer base into their operations. Columns (4) to (6) show that these results continue to hold when we additionally include year fixed effects in the specification.

In contrast, as shown in Panel B, when we run the same analysis replacing $ln(UsefulLife)$ with $ln(HHI)$, the estimated coefficients are negative and not statistically significant at any conventional level. This result suggests that conventional concentration-based measures of competition do not capture the same variation in post-acquisition profitability that is associated with the durability of customer relationships.

5.3 Share of industry profits

Taken together, our findings thus far indicate that more durable customer relationships generate persistent pricing power that results in higher gross and operating profit margins for these leading firms. In our model, these firms also capture a larger share of profits within product markets.

To test this, we estimate Equation 36 using $\Delta ProfitShare$ as the dependent variable, defined as the log change in firms' share of industry profits between $t-1$ and $t+n$, where t denotes the acquisition year. Panel A of Table 4 reports the results. Consistent with this idea, we find that as we expand the window of time from columns (1) to (3), the association between our variable of interest, the interaction between $ln(UsefulLife)$ and $Weight$, and industry profit share increases monotonically in economic magnitude and statistical significance. We find similar results when we add a year fixed effect to the specification in columns (4) to (6). In contrast, as shown in Panel B, this relationship is not reflected in standard concentration measures: when we replace $ln(UsefulLife)$ with $ln(HHI)$ and re-estimate the model, the estimated coefficients are not statistically significant.

6. Durability and Business Dynamism

In this section, we examine the implications of customer durability for business dynamism. In our model, durable customer relationships reduce dynamism through leadership entrenchment and labor market displacement. We test these predictions by examining the relationship between customer durability and changes in market structure, market entry, job reallocation, the share of employment accounted for by small firms, the labor share, and wages.

6.1 Market structure

A central implication of our model is that greater durability of customer relationships leads to higher market concentration. As leading firms raise prices above marginal cost while retaining their customer base, they expand their revenue relative to rivals. Consequently, aggregate revenue-based market concentration increases with customer durability through this direct pricing effect. Figure 7 provides visual evidence consistent with this prediction, showing a positive relationship between customer durability and industry concentration. Moreover, the relationship increases in economic magnitude as the horizon expands from $t-1$ to $t+1$ through $t-1$ to $t+4$.

To quantify this pattern more systematically, we estimate the following regression model:

$$\Delta HHI_{j,t-1,t+n} = \beta_1\, ln(UsefulLife)_{i,j,t} + \gamma_j + \tau_t + \epsilon_{i,t} \tag{37}$$

where our dependent variable, $\Delta HHI_{i,t-1,t+n}$, denotes the change in HHI for industry j between $t-1$ to $t+n$. Our HHI measure is based on economy-wide concentration indices at the six-digit NAICS level published by the U.S. Economic Census. Because these data are reported every five years, we linearly interpolate the values for missing years to construct an annual series. Our measure of customer durability, $ln(UsefulLife)$, is the natural logarithm of the useful life of customer relationship-related intangibles acquired at time t by firm i in industry j. We include industry and year fixed effects, and cluster standard errors at the industry level.

Table 5, Panel A, reports the results. Columns (1) to (3) present regressions that include industry fixed effects, while columns (4) to (6) additionally include year fixed effects. In column (1), the coefficient is positive and statistically significant at the 5% level, indicating that a one percent increase in the useful life of customer relationships in the acquisition year is associated with a 2.352 percentage point increase in HHI between $t-1$ and $t+1$. When the horizon is extended to $t+2$ in column (2), the coefficient increases in both magnitude and statistical significance, rising by 1.1 percentage points (or 46%) to 3.438. In column (3), where the window is further extended to $t+3$, the coefficient increases again to 4.401 (or 87% relative to column 1). This monotonic pattern continues as we further extend the horizon to $t + 6$, as reported in Panel C.

In Panel B, we report results from regressions that replace $ln(UsefulLife)$ with $ln(HHI)$. Across all columns, we find that, unlike customer durability, conventional HHI-based measures of market concentration are negatively associated with subsequent changes in HHI. For example, in column (3) of Panel B, the coefficient of -4.135 indicates that a one percent increase in HHI in the acquisition year is associated with an approximately 4 percentage point decline in HHI between $t - 1$ and $t + 3$. In Panel D, we extend the horizon to $t + 6$ and find that the relationship becomes increasingly negative as the window expands.[13] One plausible mechanism is that antitrust scrutiny constrains further consolidation in already concentrated industries, limiting the scope for mergers to raise concentration.[14] At the same time, high-HHI industries may be particularly attractive to potential entrants seeking to capture economic rents. Elevated entry into these markets can erode concentration over time, thereby contributing to the negative relationship we observe between current and future HHI.

6.2 Market entry and exit

6.2.1. Entry

As described in our model, when customer durability is high, it discourages the competitive efforts of followers and entrants. This prediction aligns with a well-documented pattern in the prior literature: a slowdown in new business formation in the United States, particularly among young, high-growth firms (Gourio et al., 2014; Karahan et al., 2024; Decker et al., 2016). In the next set of tests, we examine the relationship between the useful life of customer relationships and market entry.

Our measure of entry is drawn from the U.S. Census Bureau's Business Dynamics Statistics (BDS). The BDS reports annual establishment entry rates, defined as the number of establishments entering in a year divided by the average number of active establishments with employment in that year and the year before, calculated at the four-digit NAICS industry level. Table 6, Panel A, reports results of regressing $EntryRate$ on $ln(UsefulLife)$

[13] In Online Appendix I, we illustrate this relationship using plots.

[14] Consistent with this idea, the U.S. Department of Justice and Federal Trade Commission generally measure concentration using HHI, as outlined in the Merger Guidelines.

for years $t+1$ through $t+6$. Across all columns, we find a negative and statistically significant coefficient indicating that higher customer durability is associated with lower entry rates in the industry. This result is consistent with the findings in Panel A of Table 5, where HHI increases over time as the useful life of customer relationships rises, since reduced entry limits the competitive forces that would otherwise decrease market concentration.

By contrast, in Online Appendix J, we document a positive relationship between $ln(HHI)$ and $EntryRate$ across all specifications. This pattern helps rationalize the negative association between current HHI and future HHI reported in Panel B of Table 5 as arising, at least in part, from entry dynamics: as firms enter and capture market share, revenue-based measures of concentration decline.

While establishment-level data provide a broader view of entry, they may conflate new establishments created by incumbent firms with those arising from true entrants. To address this concern, we turn to firm-level data from the BDS and measure entry as the number of new firms in an industry-year that are zero years old, scaled by the total number of firms in the industry. Panel C reports the results, showing a negative and statistically significant relationship between the useful life of customer relationships and firm entry rates across all six columns. In Panel D, we show that these results remain robust to the inclusion of year fixed effects.

6.2.2. Exit

Market entry is a central force in displacing less productive incumbents, consistent with the broader process of "creative destruction" (Hopenhayne, 1992; Melitz, 2003; Foster et al., 2008; Schumpeter, 1942; Aghion and Howitt, 1992).[15] Motivated by this mechanism, we next examine whether greater customer durability is associated with lower exit rates. We conduct this analysis using the BDS, which is measured at the establishment level, as firm-level exit rates are not available in these data.

Table 7, Panel A, presents the results. We find a negative and statistically significant relationship between $ln(UsefulLife)$ and $ExitRate$, with effects that emerge in $t+1$ and persist through $t+6$. This pattern remains robust to the inclusion of year fixed effects, as shown in Panel B.

[15] Syverson (2011) provides a review of the empirical evidence.

6.3 Job reallocation

Greater durability of customer relationships allows leading firms to remain entrenched for longer, dampening innovation by followers and discouraging entry by new, innovative firms. In our theoretical framework, these forces also extend to the labor market: as competitive pressures weaken, fewer workers transition from incumbents to followers or entrants, leading to a decline in cross-firm labor reallocation.[16] Motivated by this prediction, we next examine whether higher customer durability is empirically associated with lower rates of job reallocation.

Specifically, for industry j (at the six-digit NAICS level), acquisition year t, and horizon $t+n$, we construct job reallocation rates in three steps.[17] First, we measure industry-level job creation and destruction:

$$JobCreation_{j,t+n} = max(0, Emp_{j,t+n} - Emp_{j,t-1})$$
$$JobDestruction_{j,t+n} = max(0, Emp_{j,t-1} - Emp_{j,t+n})$$

where $Emp_{j,t}$ is the number of employees in industry j at time t. Second, we scale these flows to obtain job creation and destruction rates:

$$JobCreationRate_{j,t+n} = \frac{JobCreation_{j,t+n}}{\overline{Emp}}$$
$$JobDestructionRate_{j,t+n} = \frac{JobDestruction_{j,t+n}}{\overline{Emp}}$$

where $\overline{Emp}$ is the average number of employees between $t-1$ and $t+n$ for industry j. Finally, we define the job reallocation rate as the sum of job creation and destruction rates:

$$ReallocationRate_{j,t+n} = JobCreationRate_{j,t+n} + JobDestructionRate_{j,t+n}$$

We implement this procedure using three data sources—Compustat, Revelio, and the Census BDS—each of which produces a distinct measure of job reallocation and offers complementary advantages and limitations.[18]

[16] A decline in job reallocation is a well-documented artifact of the broader slowdown in U.S. business dynamism (e.g., Davis and Haltiwanger, 2014; Decker et al., 2014, 2016).

[17] For our measure of job reallocation rates, we follow Decker et al. (2014), which follows Davis et al. (1996).

[18] Using Compustat allows us to directly match to firms in our sample, but it does not provide information on wages. Revelio includes wage data, and allows us to view reallocation rates at the employee category-level, but suffers from sample attrition as we move backward in time. The Census BDS, while covering the entire economy, cannot be linked to individual firms and also lacks wage information.

Table 8 reports results from job reallocation rates—computed with Compustat employee-headcount data—regressed on $ln(UsefulLife)$. Consistent with the predictions from our model, in Panel A, we find negative and statistically significant coefficients across all six columns, indicating that longer useful lives of customer relationships are associated with lower job reallocation. Notably, the magnitude of these associations increases (in absolute value) as we extend the window from $t-1$ to $t+1$ through $t-1$ to $t+6$. We obtain similar results in Panel B when adding year fixed effects.

In Table 9, we present results from job reallocation tests using Revelio data, which allow us to examine reallocation both in aggregate and across job categories. Panel A pools all job categories and shows a negative and statistically significant relationship between $ln(UsefulLife)$ and job reallocation rates. Panel B disaggregates the analysis by seniority level—where 1 corresponds to entry-level employees and 7 to senior management—and reveals that the magnitude of the relationship increases (in absolute value) as we move from senior leadership to entry-level workers. This pattern indicates that higher customer durability disproportionately reduces job reallocation among lower-level workers.

In Online Appendix K, we report results from regressions that employ Census BDS data to compute job reallocation rates. The BDS data are at an industry level, but allow us to capture all job reallocation activity in the economy. Consistent with the findings in Tables 8 and 9, the coefficients in Panel A are negative and statistically significant across all six columns. In Panel B, we take advantage of a measure of excess job reallocation published in the BDS data, defined as the rate of job reallocation needed to accommodate net job creation in the industry. In all columns, we find a negative and statistically significant relationship between $ln(UsefulLife)$ and excess job reallocation, indicating that industries with more durable customer relationships exhibit lower rates of job reshuffling across firms, holding net employment growth constant.

6.4 Wages

Our earlier evidence that firms with more durable customer relationships earn higher gross and operating profit margins suggests that employees capture little, if any, of these benefits. This pattern is also consistent with our findings of reduced job reallocation and fewer new entrants in such industries, as higher reallocation and entry are important for the creation of better-paying jobs. Using wage data from Revelio, we test this implication by examining whether employees at firms with more durable customer relationships experience slower wage growth.

Table 10 reports estimates from OLS regressions of the log change in salaries between $t-1$ and $t+n$—where t denotes the acquisition year—on $ln(UsefulLife)$. Panel A presents results for a pooled sample across job categories. We find a negative and statistically significant relationship, indicating that greater customer relationship durability is associated with slower wage growth. In terms of economic magnitude, the coefficient of -0.289 in column (1) implies that a 1 percent increase in useful life is associated with approximately a 0.3 percent reduction in wage growth between $t-1$ and $t+1$. Extending the horizon to $t+6$, this effect grows to roughly -1.7 percent.

Panel B reports results by seniority level. With the exception of top executives (Seniority 7), all groups exhibit a relative slowdown in wage growth, as reflected in consistently negative coefficients across columns and rows. In contrast, for the highest level of management, we estimate a positive—though statistically insignificant—relationship, suggesting that any negative wage growth effects of higher customer durability are concentrated away from top executives.

6.5 Labor share

Our findings of greater customer durability being related to higher gross margins alongside slower wage growth suggest a decline in the labor share of output (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Karabarbounis, 2024; Autor et al., 2020). Directly testing this implication, however, requires firm-level payroll data, which are not available in our setting. To address this limitation, we construct an approximation of total wage bills by combining firm-level headcount from Compustat with average industry wages estimated from Revelio data. We then scale these imputed wage bills by firm sales to obtain a proxy for labor share. Using this firm-level measure, we estimate Equation 36 with the dependent variable defined as $\Delta LaborShare$—the log change in labor share for firm i in industry j—and interact it with $Weight$, which captures the economic importance of customer relationship assets to the firm.

Table 11 reports the results. Consistent with our conjecture, we find a negative relationship between the interaction term and changes in the labor share. In Panel A, the coefficient on the interaction term becomes larger in absolute value and more statistically significant as the horizon expands, indicating that the labor share declines as the useful life of customer relationships increases, particularly when such relationships are economically important to the firm. In Panel B, we obtain qualitatively similar but somewhat weaker evidence in terms of statistical significance after including year fixed effects.

7. Durability and Innovation Dynamics

In Akcigit and Ates (2023), declining knowledge diffusion is identified as a central force behind rising market concentration and the slowdown in U.S. business dynamism. However, the paper leaves open a key question (p. 2107): what drives the decline in knowledge diffusion? We propose that an increase in the durability of customer relationships is an important contributing factor. Our evidence thus far shows that longer-lasting customer relationships are associated with lower rates of market entry and reduced job reallocation—two key channels through which knowledge diffuses across firms. Given the central role of innovation in this process, we next examine how customer durability shapes market leaders' incentives to innovate.

Our model predicts an inverted-U relationship between customer durability and innovation. At low levels of durability, firms cannot appropriate the returns to innovation for long, resulting in weak incentives to innovate. As durability increases, leading firms have stronger incentives to invest in innovation to maintain their advantage over followers and deter entry. However, at high levels of durability, competitive pressure from both followers and potential entrants declines substantially. As a result, leaders' incentives to continue innovating weaken, leading to a reduction in leaders' share of innovation and the quality of their innovations.

These predictions offer a potential explanation for several empirical patterns documented in the literature: (1) the declining relative innovative output and quality of innovation in more mature firms (Akcigit and Goldschlag, 2023); (2) the reduced frequency with which market leaders introduce new products (Argente et al., 2025); and (3) the increasing tendency of leading firms to produce innovations with only marginal contributions (Akcigit and Goldschlag, 2023).

Figure 8 illustrates the inverted-U relationship predicted by our model. Innovation, shown on the y-axis, is measured—following Aghion et al. (2005)—by firms' share of total forward citations in a given year, while the x-axis represents the log of the useful life of customer relationships. At $t+1$, where t denotes the acquisition of customer relationships, the inverted-U pattern is already evident. As the horizon extends from $t+1$ to $t+4$, the curve becomes steeper, particularly at high levels of customer durability. At the highest levels of durability, this evolution is consistent with a weakening of competitive pressure over time, which in turn reduces firms' incentives to innovate.

Next, we test these predictions empirically using measures based on the share of patents and the share of forward citations. We also examine how these effects relate to the productivity of innovators within firms and, finally, investigate investment in R&D.

7.1 Share and quality of innovation

To test the inverted-U relationship between customer durability and innovation predicted by our model, we estimate the following specification:

$$InnovationShare_{i,j,t+n} = \beta_1\, ln(\mathit{UsefulLife})_{i,j,t} + \beta_2\, ln(\mathit{UsefulLife})^2_{i,j,t} + \gamma_j + \epsilon_{i,t} \tag{38}$$

where the dependent variable, $InnovationShare$, denotes firm i's share of innovation in industry j at time $t+n$. We measure innovation share in two ways: (i) the firm's share of total patents issued in year $t+n$, denoted $PctPatents$; and (ii) the firm's share of total forward citations in year $t+n$, denoted $PctCitations$. Variable definitions are provided in Appendix A. We include our measure of customer durability, $ln(UsefulLife)$, along with its squared term, $ln(UsefulLife)^2$, to capture the nonlinear relationship. Because the sample is restricted to firms with patents, we include industry fixed effects (γ_j) but exclude year fixed effects in order to preserve sample size. Standard errors are clustered at the industry level.

Table 12 reports the results. In Panel A, which presents estimates from regressions of $PctPatents$ on the useful life of customer relationships, we find evidence consistent with an inverted-U relationship: the coefficient on $ln(UsefulLife)$ is positive and statistically significant, while the coefficient on $ln(UsefulLife)^2$ is negative and statistically significant.

Together, these estimates imply that the share of innovation initially increases with customer durability, reaches a peak, and then declines as durability becomes sufficiently high.

Panel B reports analogous regressions using $PctCitations$, corresponding to the measure depicted in Figure 6. Consistent with the graphical evidence, the coefficient on $ln(UsefulLife)$ is positive and statistically significant, while the coefficient on $ln(UsefulLife)^2$ is negative and statistically significant.

Recall that higher customer durability is associated with lower rates of job reallocation. As a result, knowledge has fewer opportunities to diffuse to followers and new entrants, consistent with the findings of Akcigit and Ates (2023). At the same time, greater customer durability weakens firms' incentives to innovate, reducing the productivity of innovation-generating employees. Consistent with this mechanism, Panel C of Table 12 shows that forward citations per innovator decline as the useful life of customer relationships increases.

7.2 Investment in research and development

Collectively, our findings in this section indicate that the durability of customer relationships plays an important role in shaping firms' innovation decisions. Firms with longer-lasting customer relationships face weaker threats of entry, which in turn dampens their incentives to develop new innovations; moreover, the innovations they do produce contribute less. A natural next question is whether customer durability is also associated with a decline in research and development (R&D) spending—a key channel through which these effects may arise. We empirically test this in the following regression model:

$$\begin{aligned}\Delta R\&D_{i,j,t-1,t+n} = {} & \beta_1\, \mathit{ln(UsefulLife)}_{i,j,t} \times \mathit{Weight}_{i,j,t} + \beta_2\, \mathit{ln(UsefulLife)}_{i,j,t} \\ & + \beta_3\, \mathit{Weight}_{i,j,t} + \gamma_j + \tau_t + \epsilon_{i,t}\end{aligned} \tag{39}$$

where our dependent variable, $\Delta R\&D_{i,t-1,t+n}$, denotes the log difference in R&D expense between $t-1$ and $t+n$, for firm i in industry j. All other variables are defined previously. We include industry fixed effects (γ) and year fixed effects (τ). Standard errors are clustered at the industry level.

Our sample is limited to firms that separately disclose R&D expenses in their financial statements, which reduces the number of observations to about 400 and declines further as we extend the window to examine the dynamics of R&D spending. Despite this loss of power, Panels A and B of Table 13 show a negative relationship between customer durability and changes in R&D spending, with coefficients that are statistically significant in columns (2) through (4). Because wages comprise more than half of R&D expenditures on average (Glaeser et al., 2025), these results are also consistent with our earlier findings of a relationship between higher customer durability and reduced wage growth and a declining labor share.

8. Conclusion

This paper studies how the durability of customer relationships shapes competition, innovation, and the allocation of economic activity. Using novel data on firms' expected useful lives of customer relationship–related intangible assets, we document a broad-based rise in customer durability in the United States over the past two decades. We then develop and test a framework in which longer-lasting customer relationships reduce the pool of contestable customers, weakening competitive pressure and reshaping firm behavior.

Our findings point to a unifying mechanism behind several prominent trends in the U.S. economy: Greater customer durability is associated with higher markups, operating profits, and profit shares, as well as increased market concentration, reduced entry and exit, lower job reallocation, slower wage growth, and a declining labor share. We also show that durability has non-monotonic effects on innovation: while moderate levels strengthen incentives to invest, high levels dampen both the quantity and quality of innovation, partly through reduced R&D spending. Taken together, these results suggest that the increasing persistence of customer relationships has important consequences not only for firm performance, but also for the dynamism of the broader economy.

More broadly, our analysis highlights the importance of moving beyond static measures of market structure when evaluating competition. Traditional metrics such as concentration indices may fail to capture a key, forward-looking dimension of market power: firms' ability to retain customers over time. By contrast, customer durability directly shapes the degree of contestability in markets and thus the intensity of competitive forces that drive entry, innovation, and resource reallocation.

These insights carry important implications for policy. As firms increasingly rely on business models that extend customer relationships—through subscriptions, loyalty programs, data-driven personalization, and ecosystem integration—understanding how these strategies affect competition becomes critical. Our results suggest that policies aimed at reducing switching frictions and preserving the contestability of customers may play an important role in sustaining competition and economic dynamism.

Finally, our work opens several avenues for future research. Understanding the determinants of rising customer durability—whether driven by technological change, firm strategy, or regulation—remains an important question. In addition, further work could explore how these dynamics vary across industries and interact with labor markets, financing conditions, and global competition. By introducing a new, forward-looking measure of customer relationships and documenting its economy-wide implications, we hope to encourage further research on this increasingly central dimension of modern markets.

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A. Variable Descriptions and Sources of Data

Notes: This table presents variable descriptions.

Explanatory Variables:

Variable	Description	Data Source
UsefulLife	Useful economic life (in years) of customer data at the acquirer–year level. We compute a weighted average of reported useful life across acquisitions of customer data, where weights are proportional to each acquisition's fair value relative to the total value of customer data acquired in that year. We obtain data on the useful life of each category of intangible capital from 10-K SEC filings.	SEC EDGAR
Weight	The ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition, expressed as a percent. The value of customer data is obtained from PPA disclosures in 10-K SEC filings. The acquiring firms' assets is obtained from Compustat.	SEC EDGAR, Compustat
HHI	Herfindahl–Hirschman index for the acquiring firm's industry, as specified by its 6-digit NAICS code in the year of the acquisition. We linearly interpolate HHI in an industry for years between 2002, 2007, 2012, 2017, and 2022.	Economic Census

Dependent Variables:

Variable	Description	Data Source
GrossMargin	Ratio of the acquirer's gross profit to its total revenue.	Compustat
EbitMargin	Ratio of the acquirer's EBIT to its total revenue.	Compustat
ReallocationRate	The sum of job creation rate and job destruction rate. The job creation or destruction rate is the number of jobs gained or lost between a given year t and t-1, scaled by the average number of jobs between years t and t-1, at the industry level. We define industries using six-digit NAICS codes.	Compustat, Revelio, Census BDS
ExcessReallocRate	The reallocation rate minus the absolute value of the net job creation rate. The net job creation rate is the job creation rate minus the job destruction rate. Census BDS data includes this measure at the six-digit NAICS level.	Census BDS
Salary	The weighted average salary for a 6-digit NAICS in a given year. Salaries are weighted by the number of employees at the most granular level of data in the Revelio Workforce Dynamics Dataset.	Revelio
EntryRate	The number establishments born during the last 12 months, scaled by the average number of establishments between years t and t-1, at the 4-digit NAICS level.	Census BDS

Variable	Description	Data Source
$PctEmp_{Age \leq 5}$	The share of industry employment accounted for by young firms, defined as firms with age less than or equal to five years. The measure is constructed as the average number of employees at young firms between years t and t-1, divided by the average total employment between years t and t–1 in a given industry and year. Industries are defined using four-digit NAICS codes.	Census BDS
PctPatents	Firm share of total patents issued in a given year, expressed as a percent. Patent counts are aggregated at the firm–year level using patent issue year.	KPSS
PctCitations	Firm share of total forward citations for its patents recorded in a given year, expressed as a percent. Citation counts are aggregated at the firm–year level using patent issue year.	KPSS
CitePerInnovator	$\frac{Citations_{i,t+n}}{Engineers_{i,t+n}}$, where *Citations* is the number of forward citations for firm i in year $t+n$, and *Engineers* is the estimated number of engineering employees for firm i and year $t+n$. Citation counts are aggregated at the firm–year level using patent issue year. Engineering employee estimations are aggregated from Revelio Workforce Dynamics data at the firm-year level.	KPSS, Revelio
PctR&D	R&D intensity in a given year, defined as R&D spending as a percent of sales in a given year. R&D and sales are measured at the firm–year level using Compustat data. Values are winsorized at the 95th percentile.	Compustat
ProfitShare	Firm EBIT in a given year t divided by industry EBIT. We total industry at the three-digit NAICS level.	Compustat
LaborsShare	$\frac{Emp_{i,t} \times Wage_{n,t}}{Revenue_{i,t}}$, where *Wage* is average Revelio industry salary at the NAICS-year level, and *Emp* and *Revenue* are firm-year employment and sales from Compustat. Payroll is scaled to millions before dividing by revenue.	Compustat, Revelio
Δ Variables	Log difference between the pre-acquisition year, t-1, and the specified post acquisition year, (e.g. t+1), expressed as a percent change.	Our calculations

Figure 1: Average Useful Life over Time (2002-2024)

Notes: This figure plots the average useful life of acquired customer data from 2002 to 2024 using 9,445 deals. Data used to plot these figures are described in Online Appendix B.

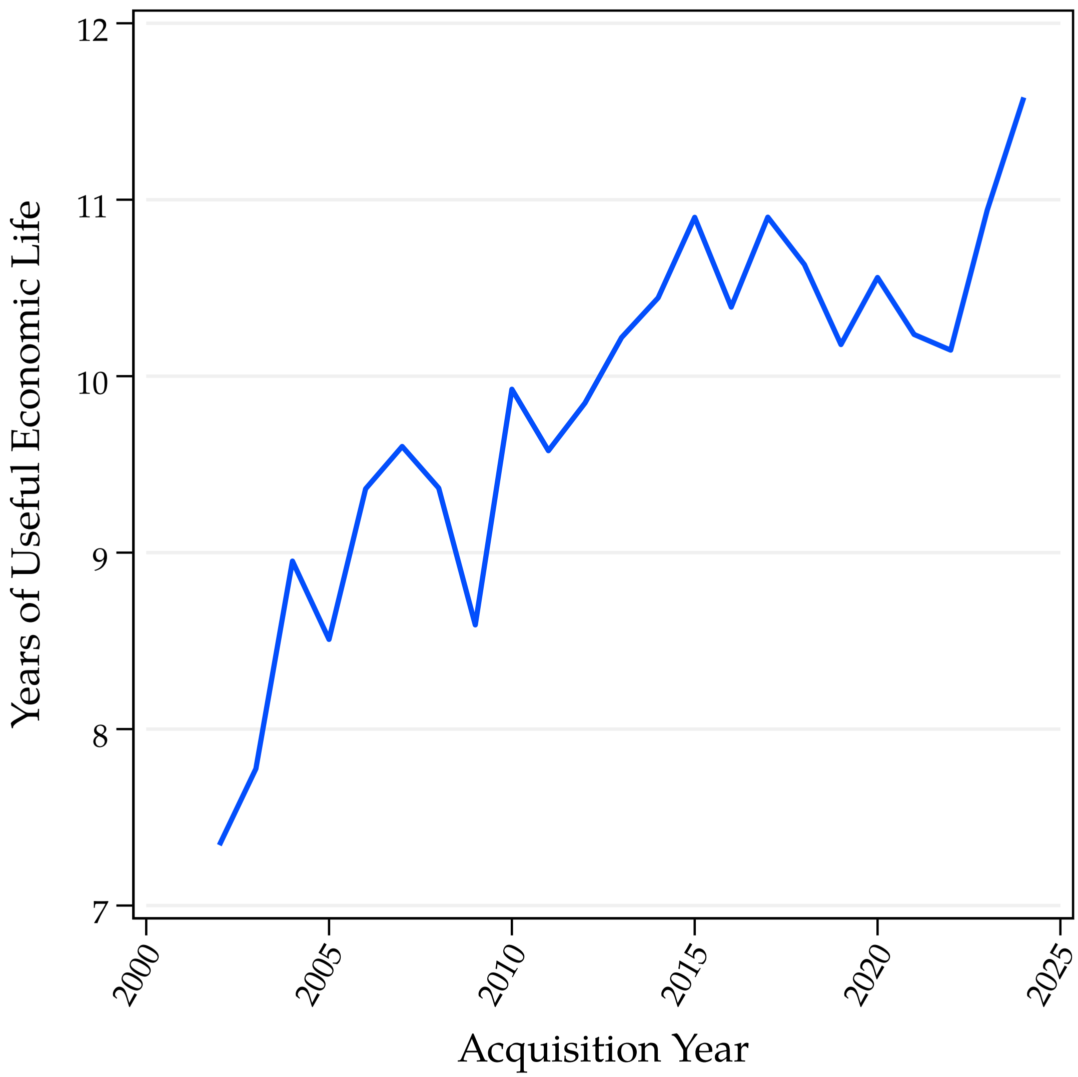


Figure 2: Average Useful Life by Industry

Notes: This figure plots the average useful life of acquired customer data from 2002 to 2024 by industry. Data used to plot these figures are described in Online Appendix B. To be included in this figure, we require that an industry averages at least ten observations per year. We use two-digit NAICS to define industries. We use the Census industry classification system to match codes to definitions as follows: NAICS 31-33 is Manufacturing; NAICS 42 is Wholesale Trade; NAICS 51 is Information; NAICS 52 is Finance and Insurance; NAICS 53 is Real Estate and Rental and Leasing; NAICS 54 is Professional, Scientific, and Technical Services; and NAICS 56 is Administrative and Support and Waste Management and Remediation Services.

Panel A. Supersectors

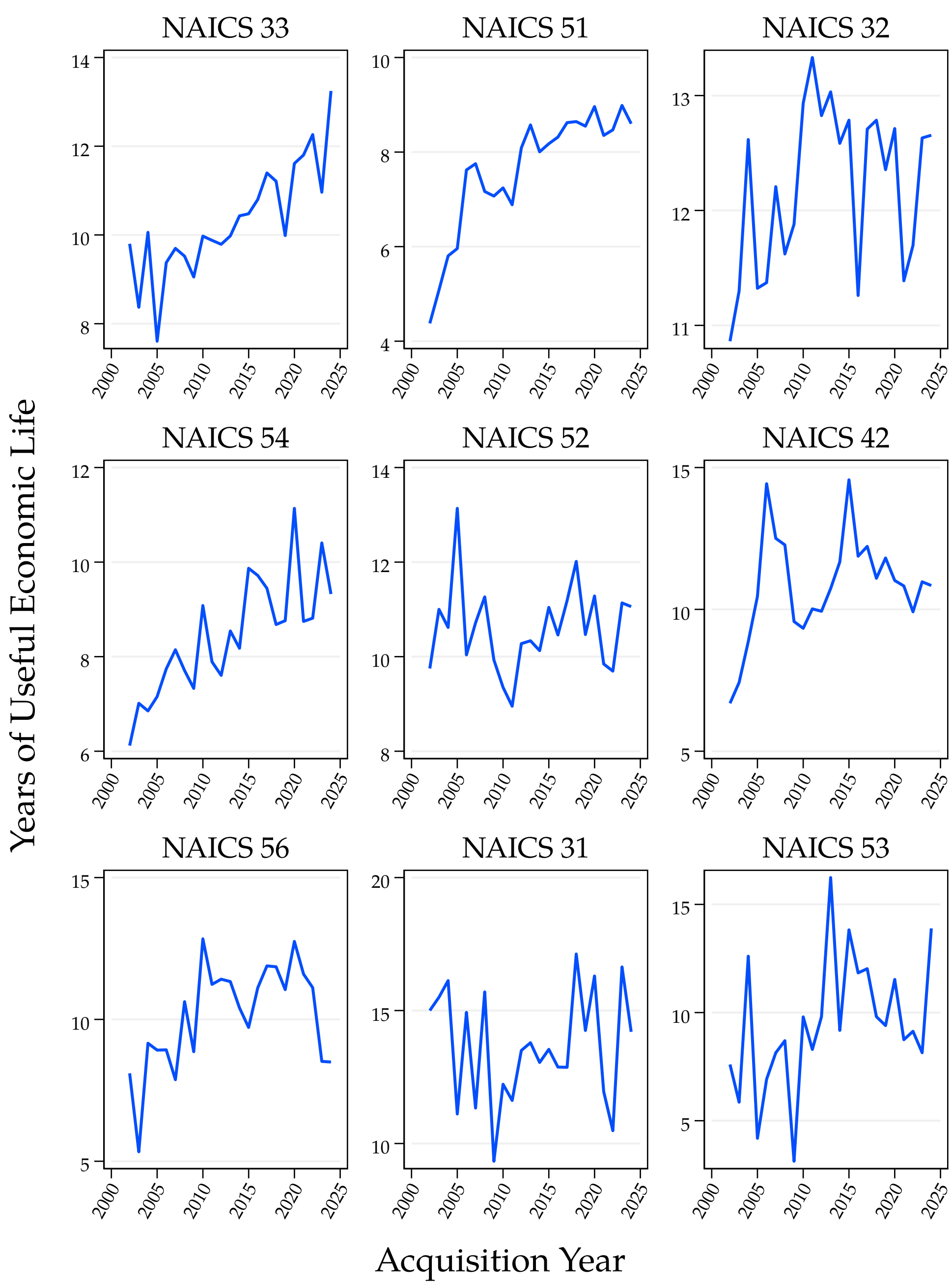


Figure 2: Average Useful Life by Industry (continued)

Panel B. Subsectors

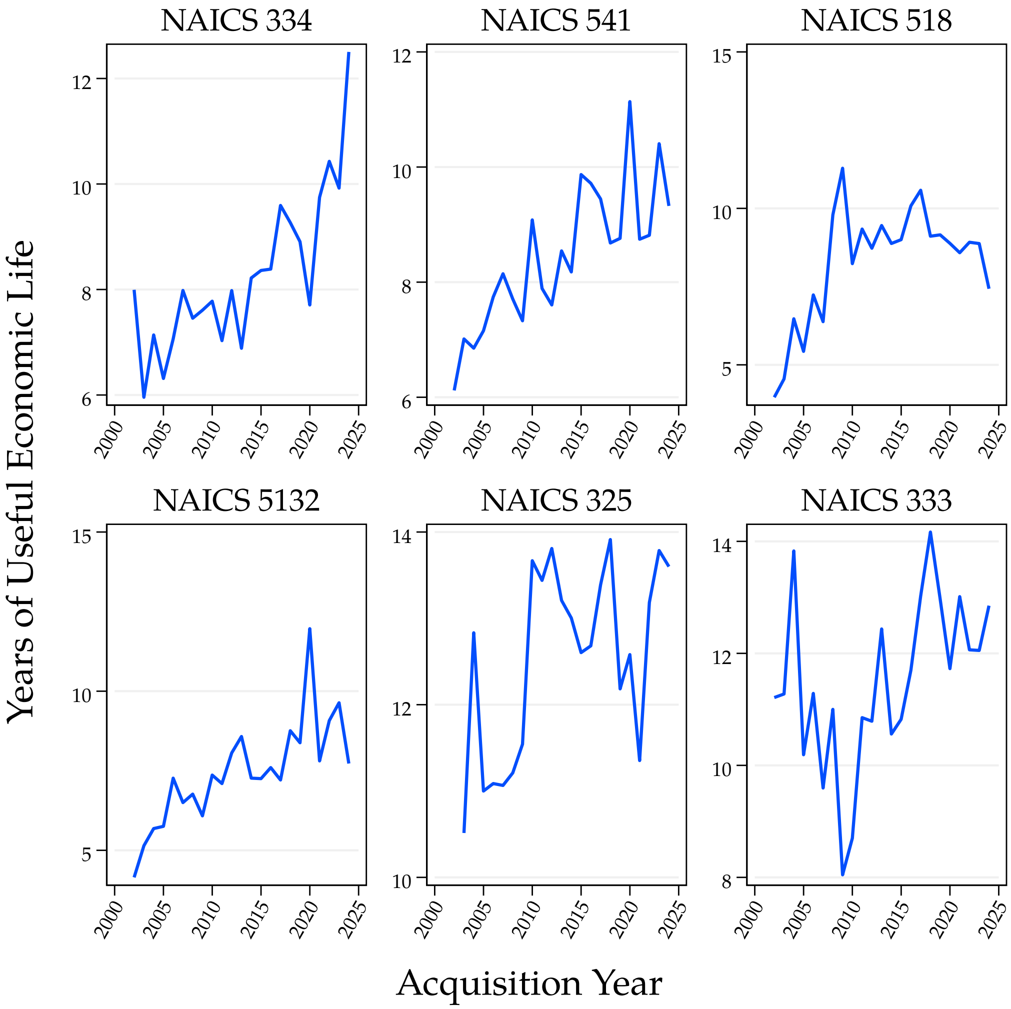
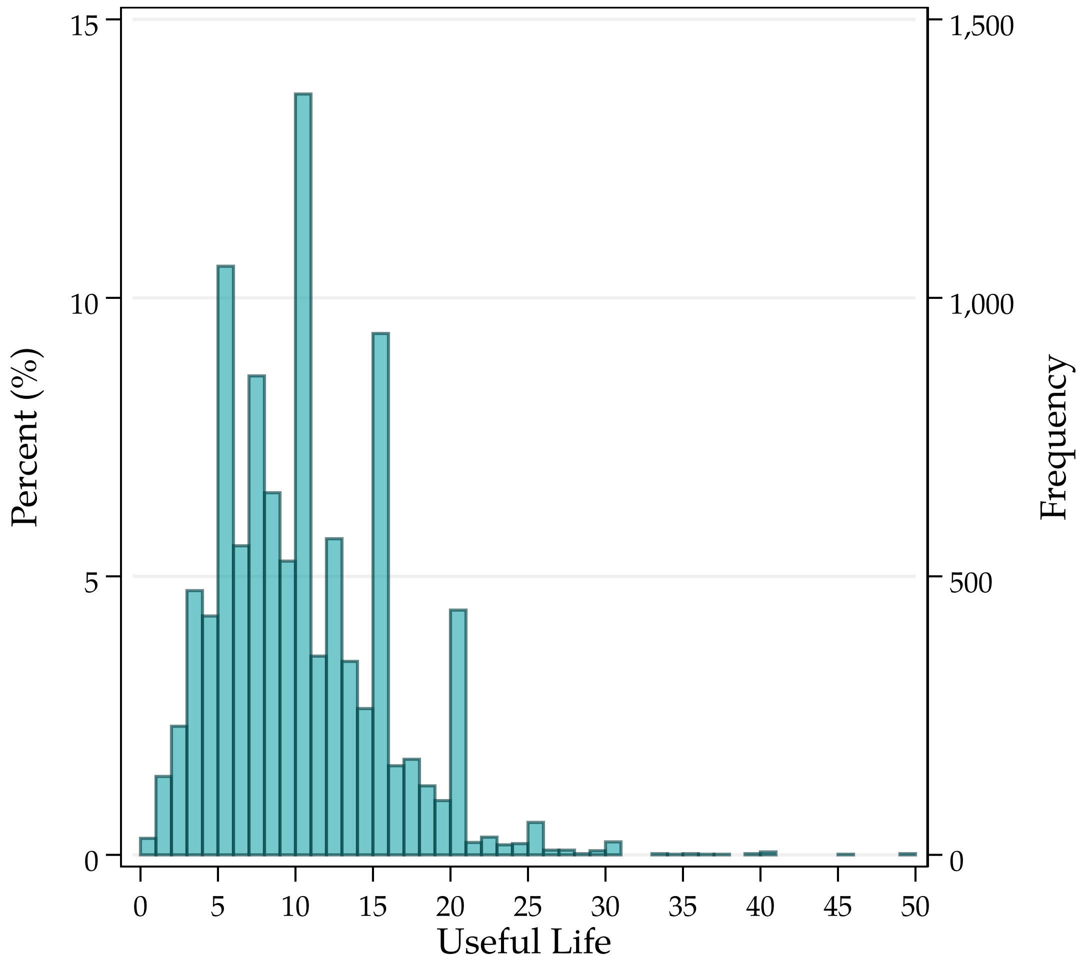


Figure 3: Distribution of Useful Life Estimates

Notes: This figure depicts the percent and frequency of useful life estimates. Bin widths are set to 1 year (i.e., [4,5), [5,6),..., [9,10)). Panel A depicts the distribution for all observations. Panel B depicts distributions at the two-digit NAICS level. We use two-digit NAICS to define industries. We use the Census industry classification system to match codes to definitions as follows: NAICS 31-33 is Manufacturing; NAICS 42 is Wholesale Trade; NAICS 51 is Information; NAICS 52 is Finance and Insurance; NAICS 53 is Real Estate and Rental and Leasing; NAICS 54 is Professional, Scientific, and Technical Services; and NAICS 56 is Administrative and Support and Waste Management and Remediation Services.

Panel A. Full Sample Distribution



Panel B. Distribution by Industry

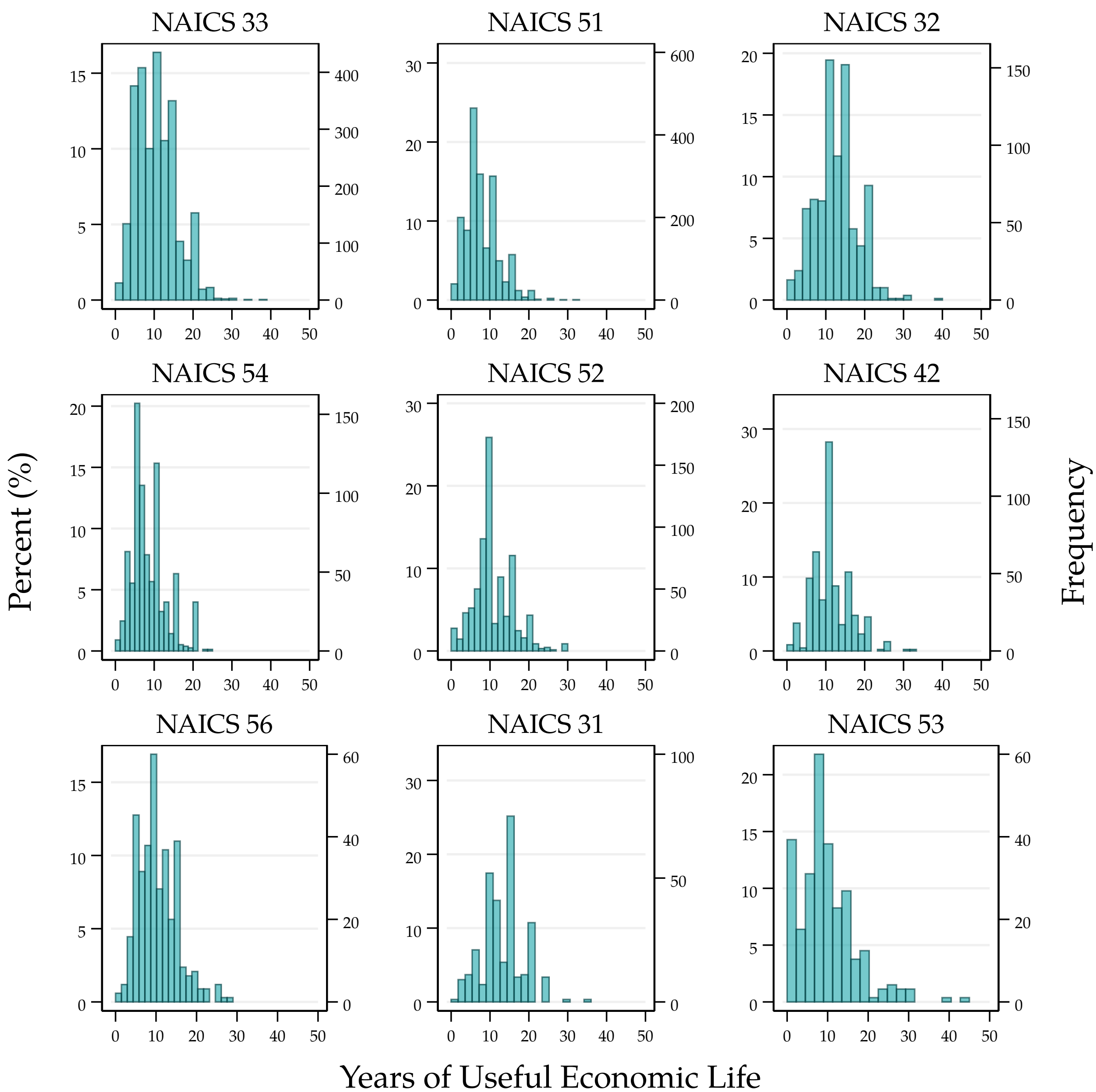


Figure 4: Useful Life and the Content of Firms' Textual Disclosures

Notes: This figure plots the relationship between the useful life of customers relationships and content of firms' textual disclosures. We plot the natural logarithm of useful life on the y-axis and the change in customer relationship durability-focused textual disclosure on the x-axis. Change in textual disclosures is measured using a bag-of-words approach. *AllWords* is the total count of key words are scaled by the total number of words. *ΔAllWords* is the log difference of this measure between year t-1 and year t+3, where t denotes the acquisition year. The our words are listed in Online Appendix E and split into seven categories: durability language, customer advocacy and loyalty signals, switching costs & customer lock-in, repeat purchasing and reorder behavior, retention and churn metrics, subscriber-base language, and stickiness language.

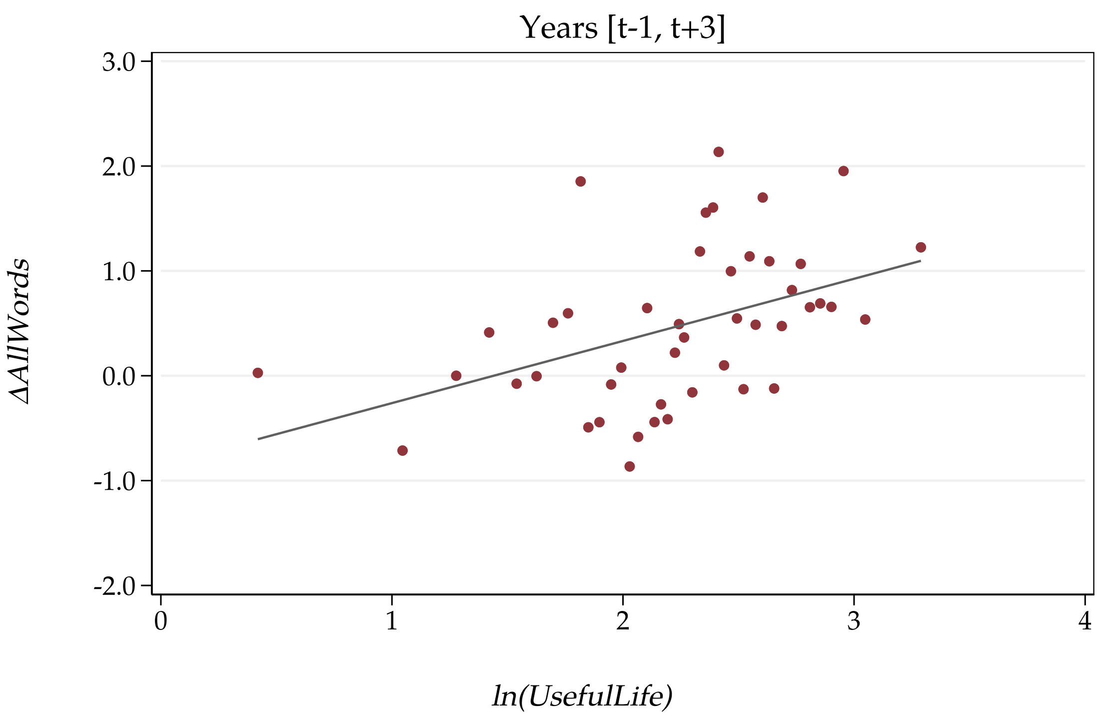


Figure 5: Average Useful Life & Gross Margins by Industry

Notes: This figure plots the mean useful life of acquired customer data and the 90th percentile of revenue-weighted gross margin from 2002 to 2024 by industry. Data used to plot these figures are described in Online Appendix B. We weight firm gross margin by the percent firm share of revenue in their industry. To be included in this figure, we require that an industry averages at least ten observations per year. We use two-digit NAICS to define industries. We use the Census industry classification system to match codes to definitions as follows: NAICS 31-33 is Manufacturing; NAICS 42 is Wholesale Trade; NAICS 51 is Information; NAICS 52 is Finance and Insurance; NAICS 53 is Real Estate and Rental and Leasing; NAICS 54 is Professional, Scientific, and Technical Services; and NAICS 56 is Administrative and Support and Waste Management and Remediation Services.

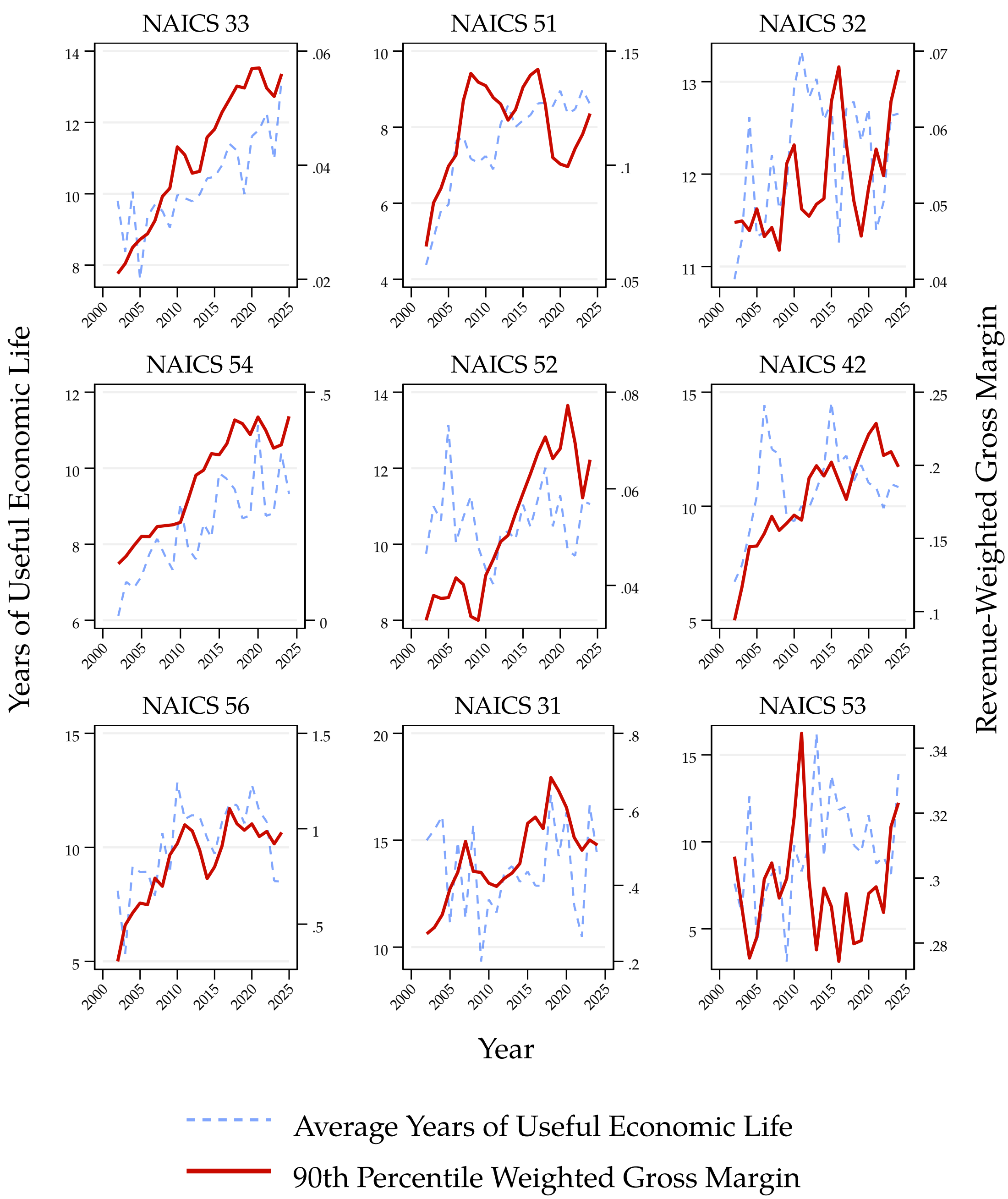


Figure 6: Average Useful Life & EBIT Margins by Industry

Notes: This figure plots the mean useful life of acquired customer data and the 90th percentile of revenue-weighted EBIT margin from 2002 to 2024 by industry. Data used to plot these figures are described in Online Appendix B. We weight firm gross margin by the percent firm share of revenue in their industry. To be included in this figure, we require that an industry averages at least ten observations per year. We use two-digit NAICS to define industries. We use the Census industry classification system to match codes to definitions as follows: NAICS 31-33 is Manufacturing; NAICS 42 is Wholesale Trade; NAICS 51 is Information; NAICS 52 is Finance and Insurance; NAICS 53 is Real Estate and Rental and Leasing; NAICS 54 is Professional, Scientific, and Technical Services; and NAICS 56 is Administrative and Support and Waste Management and Remediation Services.

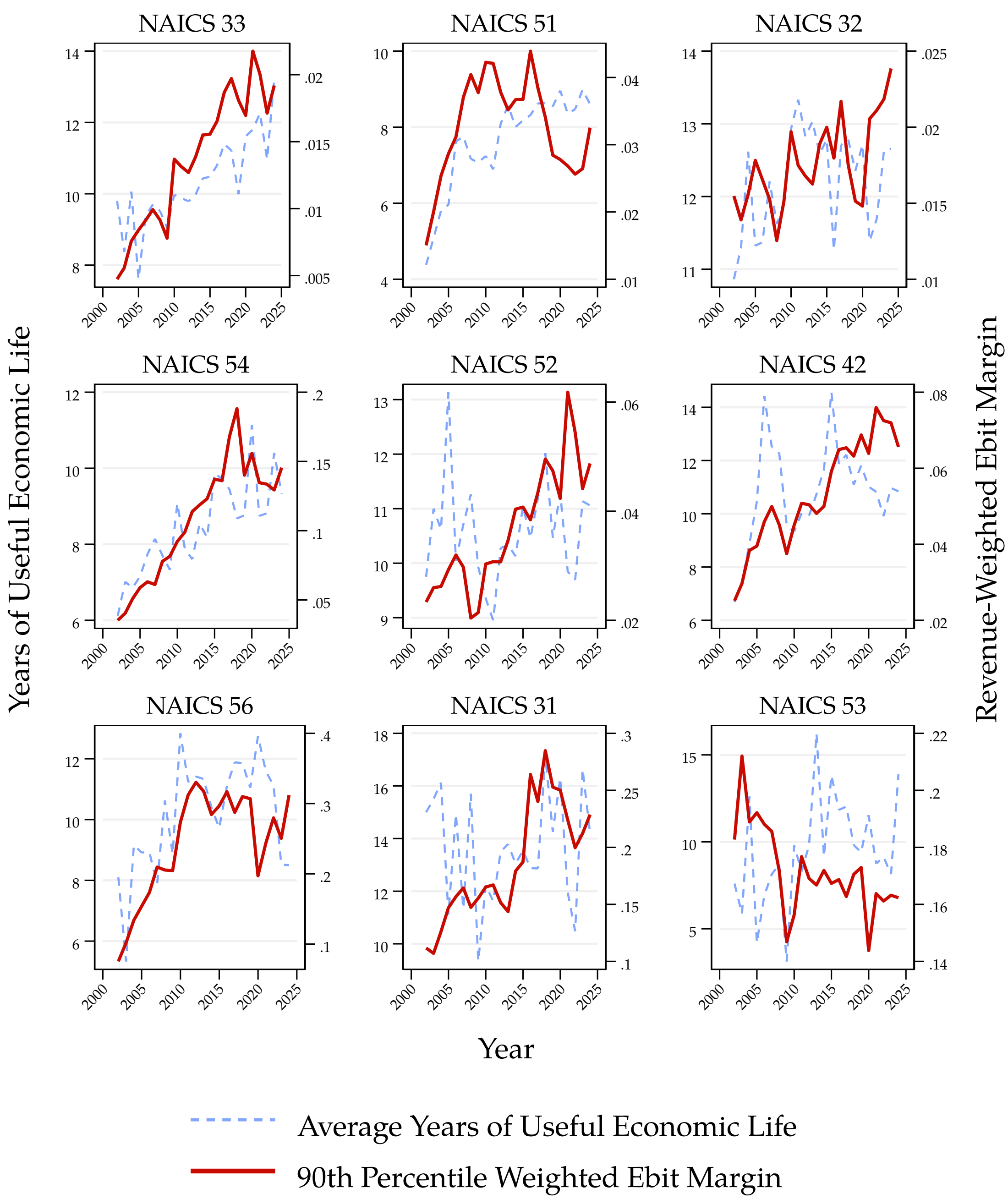


Figure 7: Forward-Looking Industry Concentration and Useful Life

Notes: These figures plot the relationship between the change in Herfindahl–Hirschman index (HHI) and the estimated useful life of customer data in the acquisition year, t. Change in HHI is the log difference in the HHI of the acquiring firm's industry between years t-1 and years t+1 through t+4. We use Binscatter to generate the figures. As such, the dots represent the average outcome for a 'bin,' where bins are created automatically by the software program, and include a "best fit" line in black.

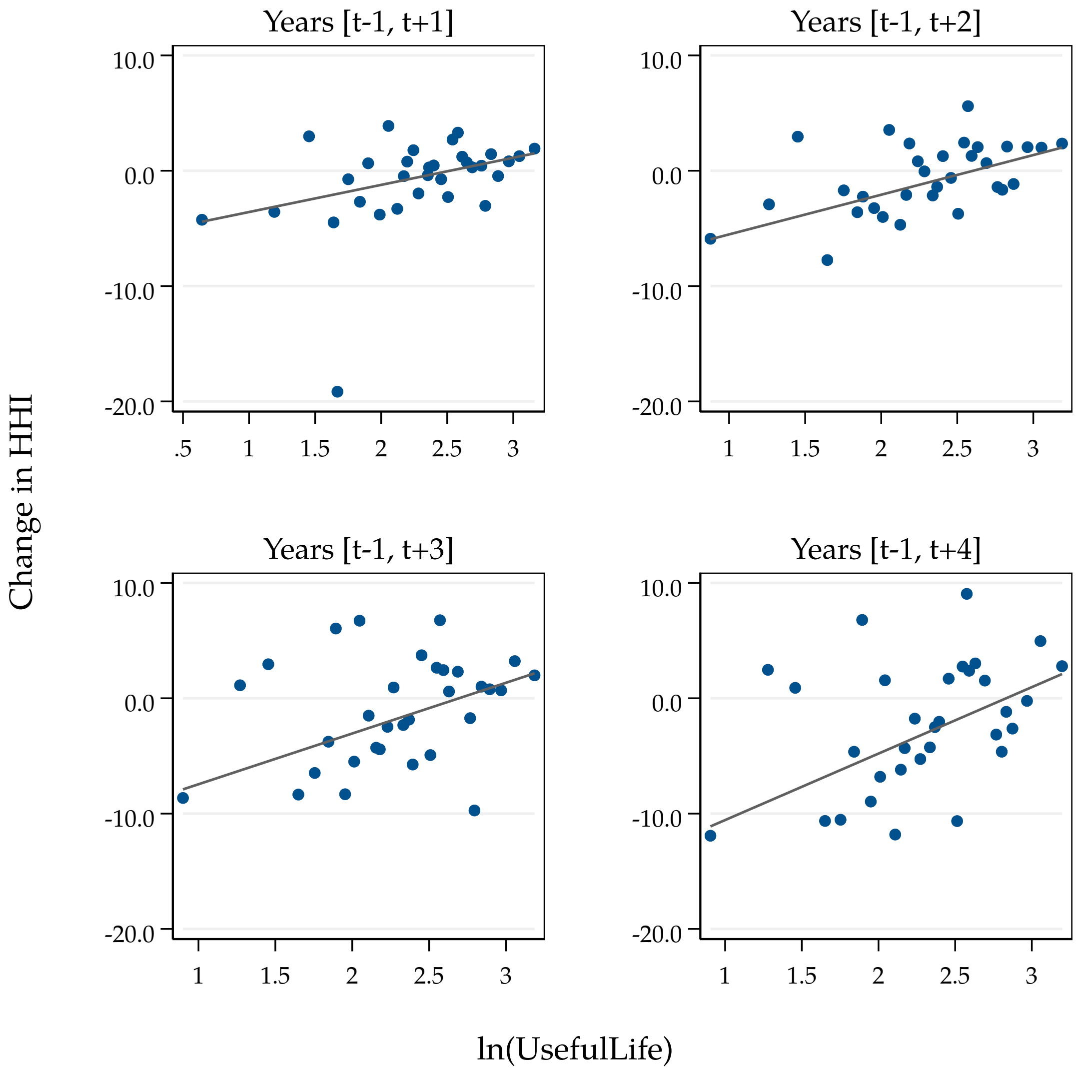


Figure 8: Inverted-U Relationship of Innovation and Useful Life

Notes: This figure plots the relationship between *PctCitations* in years t+1 through t+4 and *ln(UsefulLife)*. We use Binscatter to generate the figures. As such, the dots represent the average outcome for a 'bin,' where bins are created automatically by the software program, and include a quadratic "best fit" line in black.

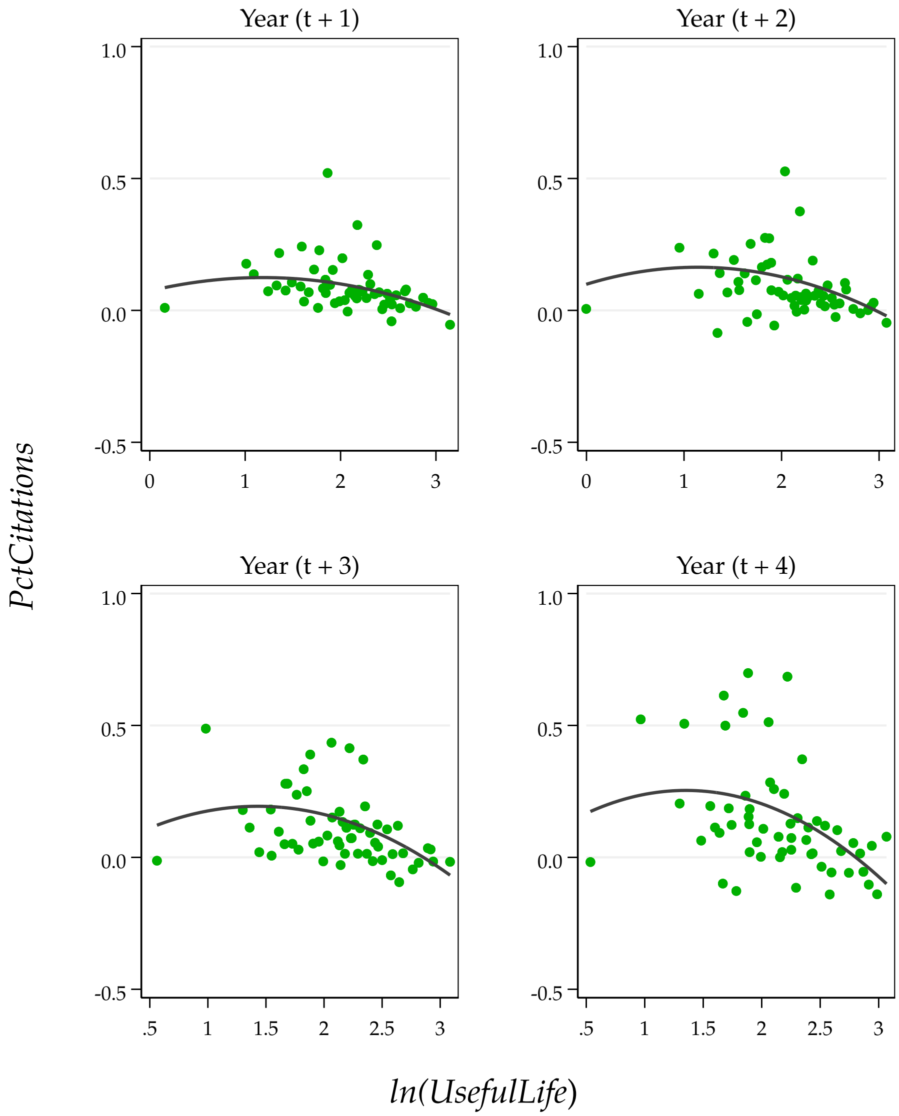


Table 1: Summary Statistics

Notes: This table presents descriptive statistics for the sample of mergers and acquisitions. Panel A reports the distribution statistics across all 9,444 deals with a reported useful life. *AcquirerSize* is the acquiring firm's total assets at the time of acquisition, in millions. *Weight* is the value of the acquired customer relationships, expressed as a percent of *AcquirerSize*. *UsefulLife* is reported in years. Panel B presents descriptive statistics by two-year acquisition period. For each period we report: the number of observations (N), the share of the full sample represented by that period (% Sample), and the standard deviation of useful life within the period (SD). To characterize acquisition activity at the firm level, we separately report statistics for firms completing multiple acquisitions in the same two-year period. $N_{multiple}$ is the number of observations associated with firms that make multiple deals in that period, and $\%_{multiple}$ is that count expressed as a percentage of all deals in the period. $\overline{SD}_{multiple}$ reports the average within-firm standard deviation of customer useful life across firms with multiple acquisitions, capturing heterogeneity in estimated useful life among repeated deals by the same acquirer. Panel C reports the distribution of customer useful life by industry, defined by two-digit NAICS codes.

Panel A. Mergers

Variable:	N	Mean	SD	p10	p25	p50	p75	p90
AcquirerSize ($M)	8,659	7,861	41,614.3	107	386	1,253	3,791	12,504
PurchasePrice ($M)	9,431	519	2,650.6	4.6	14.8	55.3	232	795
Weight	8,639	2.55	8.7	.0804	.245	.825	2.59	6.29
Customers ($M)	9,421	113	700.6	.6	2	8.4	37.1	154
UsefulLife	9,444	10	5.3	4	6	10	13.2	17

Panel B. Useful Life by Acquisition Year

Time Period	N	% Sample	SD	$N_{multiple}$	$\%_{mulitple}$	$\overline{SD}_{multiple}$
2002-2003	357	3.78 %	5.34	152	42.58 %	1.71
2004-2005	755	7.99 %	5.65	408	54.04 %	1.73
2006-2007	852	9.02 %	5.28	508	59.62 %	1.77
2008-2009	638	6.76 %	4.77	331	51.88 %	1.59
2010-2011	810	8.58 %	5.67	460	56.79 %	1.75
2012-2013	775	8.21 %	5.30	436	56.26 %	2.00
2014-2015	959	10.15 %	5.63	595	62.04 %	1.74
2016-2017	846	8.96 %	4.59	507	59.93 %	1.64
2018-2019	920	9.74 %	5.03	556	60.43 %	1.54
2020-2021	1,216	12.88 %	5.14	791	65.05 %	1.62
2022-2023	969	10.26 %	4.98	464	47.88 %	1.71
2024-2025	347	3.67 %	5.32	126	36.31 %	1.58
Total	9,444	100.00 %	5.29	5,334	56.48 %	1.70

Table 1: Summary Statistics (continued)

Panel C. Useful Life by Industry

NAICS	Industry	Mean	N	% Sample	SD	p10	p25	p50	p75	p90	Mode
33	Manufacturing	10.42	2,656	28.12 %	5.18	4.6	6	10	14.5	18	10
51	Information	7.80	1,914	20.27 %	4.18	3	5	7	10	14	5
32	Manufacturing	12.30	797	8.44 %	5.27	5	9	12	15	20	10
54	Professional, Scientific, and Technical Services	8.40	776	8.22 %	4.39	3	5	7	10	15	10
52	Finance and Insurance	10.61	692	7.33 %	5.00	5	8	10	14	17	9
42	Wholesale Trade	11.05	478	5.06 %	4.83	5	8	10	14.5	17.5	10
56	Administrative, Support, Waste Management, and Remediation Services	10.45	337	3.57 %	4.82	5	6.5	10	13.5	15.4	10
31	Manufacturing	13.27	298	3.16 %	5.22	7	10	13.25	15	20	15
53	Real Estate and Rental and Leasing	9.70	266	2.82 %	6.86	2	5	8	13	18.33	7
48	Transportation and Warehousing	12.25	179	1.90 %	6.24	5	8	10.5	15	20	15
62	Health Care and Social Assistance	10.71	173	1.83 %	5.11	4.5	7	10	14	18.6	10
21	Mining, Quarrying, and Oil and Gas Extraction	13.08	131	1.39 %	8.41	4	7	12.5	15	23	15
23	Construction	10.49	130	1.38 %	4.26	5.3	7.5	10	12	15	10
44	Retail Trade	9.11	128	1.36 %	4.45	4	5.5	9	10.75	15	10
45	Retail Trade	9.06	106	1.12 %	5.63	3	4.8	7	13	20	5
71	Arts, Entertainment, and Recreation	7.45	85	0.90 %	4.42	2.5	3	6	11	15	3
22	Utilities	13.34	80	0.85 %	8.28	4.5	7.75	12	15	20	15
61	Educational Services	5.12	60	0.64 %	3.07	2	3	5	5.87	10	5
72	Accommodation and Food Services	10.56	45	0.48 %	5.61	4	5.8	10	15	15.5	15
99	Unclassifiable Establishments	8.69	37	0.39 %	4.45	3	7	8	10	15	8
81	Other Services (except Public Administration)	7.25	35	0.37 %	3.20	3	5	7	10	11.7	7
11	Agriculture, Forestry, Fishing and Hunting	11.88	32	0.34 %	4.92	7	8	11.5	14	20	11.5
49	Transportation and Warehousing	11.81	9	0.10 %	3.22	5	10	12	14.8	15	15
.	Total	10.00	9,444	100.00 %	5.29	4	6	10	13.23	17	10

Table 2: Changes in Gross Margin

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in gross margin on two sets of explanatory variables. *Weight* is the ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition. The unit of observation is at the acquirer-year level. In Panel A, the explanatory variables are the log of useful life of customer data (*ln(UsefulLife)*), its weight (*Weight*), and their multiplicative interaction (*ln(UsefulLife)* × *Weight*). In Panel B, our explanatory variables are the log of the Herfindahl–Hirschman index, (*ln(HHI)*), the weight of the acquired customer data (*Weight*), and their multiplicative interaction (*ln(HHI)* × *Weight*). The dependent variable, Δ*GrossMargin*, is defined as the log difference in gross margin between year t-1 and future years t+1 through t+3, where t denotes the acquisition year. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in gross margin. All variables are described in Appendix A. In both panels, columns (1) through (3), we include industry fixed effects. In columns (4) through (6), we include industry and year fixed effects. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Changes in Gross Margin Explained by Useful Life

Dependent Variable: Δ*GrossMargin*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	0.305**	0.534**	0.389**	0.299**	0.518**	0.364**
	(2.48)	(2.78)	(2.30)	(2.43)	(2.70)	(2.22)
Weight	-0.697**	-1.277**	-0.816*	-0.681**	-1.242**	-0.770*
	(-2.14)	(-2.58)	(-2.02)	(-2.10)	(-2.47)	(-1.96)
ln(UsefulLife)	-0.440	-1.130	-1.166	-0.468	-1.250	-1.463
	(-0.92)	(-1.43)	(-1.07)	(-0.98)	(-1.50)	(-1.26)
Observations	5,585	4,953	4,289	5,585	4,953	4,289
Adjusted R^2	0.003	0.005	0.008	0.005	0.007	0.011
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel B. Changes in Gross Margin Explained by HHI

Dependent Variable: Δ*GrossMargin*	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI) × *Weight*	0.133*	0.0832	-0.103	0.131*	0.0789	-0.112
	(1.97)	(0.97)	(-0.79)	(1.96)	(0.93)	(-0.87)
Weight	-0.777*	-0.460	0.624	-0.756*	-0.415	0.663
	(-2.07)	(-0.84)	(0.81)	(-2.02)	(-0.78)	(0.87)
ln(HHI)	0.133	0.218	0.567	0.183	0.244	0.611
	(0.42)	(0.62)	(1.12)	(0.52)	(0.62)	(1.16)
Observations	4,471	4,231	3,594	4,471	4,231	3,594
Adjusted R^2	0.006	0.003	0.005	0.008	0.008	0.008
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Table 3: Changes in EBIT Margin

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in EBIT margin on two sets of explanatory variables. *Weight* is the ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition. The unit of observation is at the acquirer-year level. In Panel A, the explanatory variables are the log of useful life of customer data (*ln(UsefulLife)*), its weight (*Weight*), and their multiplicative interaction (*ln(UsefulLife)* × *Weight*). In Panel B, our explanatory variables are the log of the Herfindahl–Hirschman index, (*ln(HHI)*), the weight of the acquired customer data (*Weight*), and their multiplicative interaction (*ln(HHI)* × *Weight*). The dependent variable, Δ*EBITMargin*, is defined as the log difference in EBIT margin between year t-1 and future years t+1 through t+3, where t denotes the acquisition year. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in EBIT margin. All variables are described in Appendix A. In both panels, columns (1) through (3), we include industry fixed effects. In columns (4) through (6), we include industry and year fixed effects. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Changes in EBIT Margin Explained by Useful Life

Dependent Variable: Δ*EbitMargin*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	0.910	1.409*	2.500***	0.876	1.327*	2.378***
	(1.19)	(1.82)	(7.02)	(1.14)	(1.76)	(6.77)
Weight	-3.119	-4.446**	-7.416***	-3.045	-4.214**	-7.143***
	(-1.53)	(-2.27)	(-7.25)	(-1.49)	(-2.21)	(-7.19)
ln(UsefulLife)	2.475	1.773	0.298	3.006	1.992	0.327
	(0.97)	(0.62)	(0.11)	(1.25)	(0.64)	(0.11)
Observations	4,508	4,005	3,513	4,508	4,005	3,513
Adjusted R^2	0.006	0.006	0.014	0.017	0.013	0.020
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel B. Changes in EBIT Margin Explained by HHI

Dependent Variable: Δ*EbitMargin*	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI) × *Weight*	-0.0401	-0.0669	-0.262	-0.0541	-0.0460	-0.236
	(-0.20)	(-0.36)	(-0.82)	(-0.25)	(-0.25)	(-0.72)
Weight	-0.390	-0.238	0.827	-0.329	-0.332	0.676
	(-0.31)	(-0.20)	(0.46)	(-0.25)	(-0.27)	(0.36)
ln(HHI)	-0.292	1.124	1.288	-0.118	1.340	1.485
	(-0.35)	(1.38)	(1.23)	(-0.13)	(1.58)	(1.23)
Observations	3,598	3,402	2,899	3,598	3,402	2,899
Adjusted R^2	0.003	0.004	0.012	0.018	0.014	0.022
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Table 4: Changes in Industry Profit Share

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in profit share on two sets of explanatory variables. *Weight* is the ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition. The unit of observation is at the acquirer-year level. In Panel A, the explanatory variables are the log of useful life of customer data (*ln(UsefulLife)*), its weight (*Weight*), and their multiplicative interaction (*ln(UsefulLife)* × *Weight*). In Panel B, our explanatory variables are the log of the Herfindahl–Hirschman index, (*ln(HHI)*), the weight of the acquired customer data (*Weight*), and their multiplicative interaction (*ln(HHI)* × *Weight*). The dependent variable, Δ*ProfitShare*, is defined as the log difference in profit share between year t-1 and future years t+1 through t+3, where t denotes the acquisition year. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in profit share. All variables are described in Appendix A. In both panels, columns (1) through (3), we include industry fixed effects. In columns (4) through (6), we include industry and year fixed effects. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Changes Profit Share and Useful Life

Dependent Variable: Δ*ProfitShare*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	0.424	0.547	1.807***	0.427	0.896	1.611***
	(0.58)	(0.81)	(3.18)	(0.60)	(1.28)	(3.25)
Weight	0.524	0.261	-2.905	0.467	-0.647	-2.474
	(0.28)	(0.15)	(-1.66)	(0.25)	(-0.36)	(-1.58)
ln(UsefulLife)	1.373	2.906	0.505	2.795	3.284	1.746
	(0.41)	(1.05)	(0.14)	(0.98)	(1.14)	(0.55)
Observations	4,506	4,003	3,511	4,506	4,003	3,511
Adjusted R^2	0.008	0.014	0.011	0.039	0.044	0.050
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel B. Changes Profit Share and HHI

Dependent Variable: Δ*ProfitShare*	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI) × *Weight*	0.0436	0.122	-0.145	0.0525	0.114	-0.0565
	(0.10)	(0.31)	(-0.19)	(0.12)	(0.30)	(-0.08)
Weight	0.822	0.461	1.944	0.746	0.498	1.491
	(0.31)	(0.19)	(0.48)	(0.28)	(0.21)	(0.42)
ln(HHI)	-0.189	0.857	0.968	-0.188	0.882	0.689
	(-0.15)	(0.59)	(0.44)	(-0.14)	(0.57)	(0.32)
Observations	3,596	3,400	2,897	3,596	3,400	2,897
Adjusted R^2	0.004	0.008	0.009	0.010	0.021	0.047
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Table 5: Changes in HHI

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in HHI on two sets of explanatory variables. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. In Panels A and C, the explanatory variable is *ln(UsefulLife)* . In Panels B and D, the explanatory variable is *ln(HHI)*. The dependent variable, ΔHHI, is defined as the log difference in HHI for an industry-year between year t-1 and future years, where t denotes the acquisition year. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in HHI. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Change in HHI and Useful Life

Dependent Variable: ΔHHI	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	2.352**	3.438***	4.401***	2.253***	3.353***	4.030***
	(2.82)	(3.30)	(3.42)	(3.37)	(3.62)	(3.90)
Observations	2,618	2,256	2,042	2,618	2,256	2,042
Adjusted R^2	0.036	0.037	0.040	0.081	0.068	0.070
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel B. Change in HHI and Current HHI

Dependent Variable: ΔHHI	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI)	-1.082	-2.446**	-4.135**	-1.086	-2.439**	-4.094**
	(-1.57)	(-2.11)	(-2.52)	(-1.70)	(-2.25)	(-2.73)
Observations	4,531	3,925	3,540	4,531	3,925	3,540
Adjusted R^2	0.054	0.054	0.066	0.082	0.080	0.088
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel C. Change in HHI and Useful Life - Expanded Time Period

Dependent Variable: ΔHHI	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	2.352**	3.438***	4.401***	5.763***	6.382	7.297
	(2.82)	(3.30)	(3.42)	(3.12)	(2.33)	(2.21)
Observations	2,618	2,256	2,042	1,805	1,574	1,433
Adjusted R^2	0.036	0.037	0.040	0.031	0.014	0.016
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Panel D. Change in HHI and Current HHI - Expanded Time Period

Dependent Variable: ΔHHI	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI)	-1.082	-2.446**	-4.135**	-6.196**	-8.363	-10.19
	(-1.57)	(-2.11)	(-2.52)	(-2.64)	(-2.37)	(-2.62)
Observations	4,531	3,925	3,540	3,126	2,710	2,488
Adjusted R^2	0.054	0.054	0.066	0.072	0.066	0.082
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Table 6: Firm Entry Rates

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses the establishment entry rate, *EntryRate*, and the firm entry rate, *FirmEntryRate*, on *ln(UsefulLife)*. *EntryRate* is reported by Census BDS by industry for future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. In Panels A and C, we include industry fixed effects. In Panel B and D, we include industry and year fixed effects. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in firm entry rates. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Entry Rate – Industry Fixed Effects

Dependent Variable: *EntryRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.428***	-0.509***	-0.471***	-0.528***	-0.410***	-0.365***
	(-4.12)	(-4.69)	(-3.72)	(-3.50)	(-3.03)	(-2.92)
Observations	6,122	5,734	5,245	4,960	4,636	4,315
Adjusted R^2	0.463	0.487	0.514	0.545	0.545	0.549
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Panel B. Entry Rate – Industry and Year Fixed Effects

Dependent Variable: *EntryRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.282***	-0.381***	-0.356***	-0.457***	-0.412***	-0.380***
	(-2.89)	(-3.82)	(-3.54)	(-3.98)	(-4.04)	(-3.16)
Observations	6,122	5,734	5,245	4,960	4,636	4,315
Adjusted R^2	0.487	0.510	0.528	0.559	0.556	0.561
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Panel C. Firm Entry Rate – Industry Fixed Effects

Dependent Variable: *FirmEntryRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.300***	-0.328***	-0.337**	-0.402***	-0.373***	-0.360**
	(-3.17)	(-2.91)	(-2.84)	(-3.20)	(-2.86)	(-2.79)
Observations	6,121	5,733	5,241	4,957	4,630	4,310
Adjusted R^2	0.470	0.480	0.498	0.510	0.516	0.518
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Panel D. Firm Entry Rate – Industry and Year Fixed Effects

Dependent Variable: *FirmEntryRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.254**	-0.303***	-0.322**	-0.420***	-0.435***	-0.449***
	(-2.71)	(-2.91)	(-2.76)	(-3.64)	(-3.38)	(-2.90)
Observations	6,121	5,733	5,241	4,957	4,630	4,310
Adjusted R^2	0.482	0.491	0.506	0.518	0.526	0.531
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Table 7: Exit Rates

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses the establishment exit rate, *ExitRate*, *ln(UsefulLife)*. *ExitRate* is reported by Census BDS by industry for future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. In Panels A and C, we include industry fixed effects. In Panel B and D, we include industry and year fixed effects. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in firm entry rates. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Exit Rate – Industry Fixed Effects

Dependent Variable: *ExitRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.661***	-0.727***	-0.610***	-0.666***	-0.663***	-0.587***
	(-5.92)	(-8.18)	(-4.32)	(-4.63)	(-6.10)	(-4.98)
Observations	6,120	5,733	5,241	4,961	4,633	4,314
Adjusted R^2	0.429	0.455	0.448	0.448	0.437	0.449
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Panel B. Exit Rate – Industry and Year Fixed Effects

Dependent Variable: *ExitRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.482***	-0.572***	-0.500***	-0.553***	-0.532***	-0.486***
	(-3.80)	(-5.91)	(-3.91)	(-3.96)	(-4.29)	(-3.97)
Observations	6,120	5,733	5,241	4,961	4,633	4,314
Adjusted R^2	0.481	0.502	0.496	0.492	0.489	0.485
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Table 8: Compustat Estimated Reallocation Rates

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses job reallocation rates on *ln(UsefulLife)*. We compute *ReallocationRate* using Compustat employee counts between year t-1 and future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. In Panel A, we include industry fixed effects. In Panel B, we include industry and year fixed effects. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in the reallocation rate. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Industry Fixed Effects

Dependent Variable: *ReallocationRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-1.273**	-1.653*	-2.058**	-2.438**	-4.167***	-5.024***
	(-2.21)	(-1.98)	(-2.25)	(-2.50)	(-3.72)	(-2.89)
Observations	5,741	5,096	4,413	3,727	3,301	2,879
Adjusted R^2	0.020	0.031	0.041	0.059	0.080	0.070
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Panel B. Industry and Year Fixed Effects

Dependent Variable: *ReallocationRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.788	-1.004	-1.322	-1.805*	-3.814***	-4.663***
	(-1.47)	(-1.48)	(-1.54)	(-1.96)	(-3.67)	(-2.96)
Observations	5,741	5,096	4,413	3,727	3,301	2,879
Adjusted R^2	0.029	0.041	0.049	0.065	0.084	0.075
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Table 9: Revelio Estimated Reallocation Rates

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses job reallocation rates on *ln(UsefulLife)*. In Panel A, we compute *ReallocationRate* using Revelio employee counts between year t-1 and future years t+1 through t+6, where t denotes the acquisition year. In Panel B, we compute *ReallocationRate* at the Revelio-defined seniority level. Seniority 1 corresponds to the most junior roles (i.e., entry-level positions such as interns, trainees, and paralegals), while Seniority 7 corresponds to the most senior roles (i.e., top executive positions such as CEO and COO). All variables are described in Appendix A. The unit of observation is at the acquirer-year level. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in the reallocation rate. In both panels, we include industry fixed effects and cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Useful Life and Reallocation

Dependent Variable: *ReallocationRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-1.002***	-1.304***	-1.763***	-2.108***	-2.697***	-3.445***
	(-4.20)	(-4.00)	(-4.01)	(-3.07)	(-3.02)	(-2.99)
Observations	4,119	3,832	3,443	2,966	2,703	2,409
Adjusted R^2	0.173	0.194	0.207	0.218	0.224	0.237
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Panel B. Useful Life and Reallocation by Seniority

Dependent Variable: *ReallocationRate*	(1)	(2)	(3)	(4)	(5)	(6)
Seniority 1 - *ln(UsefulLife)*	-1.093***	-1.564***	-2.061***	-2.456***	-3.045***	-3.971***
	(-3.41)	(-4.05)	(-4.25)	(-3.19)	(-3.35)	(-3.84)
Seniority 2 - *ln(UsefulLife)*	-1.162***	-1.510***	-2.032***	-2.565***	-3.488***	-4.683***
	(-3.81)	(-4.00)	(-4.25)	(-3.50)	(-3.79)	(-3.99)
Seniority 3 - *ln(UsefulLife)*	-0.887***	-1.250***	-1.711***	-2.297***	-2.813***	-3.523***
	(-3.98)	(-3.44)	(-3.60)	(-2.97)	(-2.90)	(-3.05)
Seniority 4 - *ln(UsefulLife)*	-0.643***	-0.977***	-1.452***	-1.700**	-2.162***	-2.834***
	(-2.86)	(-3.23)	(-3.44)	(-2.77)	(-3.02)	(-3.59)
Seniority 5 - *ln(UsefulLife)*	-0.681***	-1.070***	-1.790***	-2.336***	-3.215***	-4.256***
	(-3.31)	(-4.11)	(-4.58)	(-4.15)	(-4.09)	(-3.68)
Seniority 6 - *ln(UsefulLife)*	-0.768*	-0.686	-1.026	-1.256	-2.127*	-2.980**
	(-2.07)	(-1.34)	(-1.59)	(-1.46)	(-1.97)	(-2.40)
Seniority 7 - *ln(UsefulLife)*	-0.00691	-0.131	-0.426	-0.764**	-1.161***	-1.498***
	(-0.04)	(-0.53)	(-1.52)	(-2.46)	(-3.47)	(-3.96)
Adjusted R^2	0.037	0.037	0.032	0.041	0.044	0.053
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Table 10: Change in Revelio Estimated Wages

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in average wages on *ln(UsefulLife)*. In Panel A, we compute Δ*Salary* using Revelio employee wages between year t-1 and future years t+1 through t+6, where t denotes the acquisition year. In Panel B, we compute Δ*Salary* at the Revelio-defined seniority level. Seniority 1 corresponds to the most junior roles (i.e., entry-level positions such as interns, trainees, and paralegals), while Seniority 7 corresponds to the most senior roles (i.e., top executive positions such as CEO and COO). All variables are described in Appendix A. The unit of observation is at the acquirer-year level. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in wages. In both panels, we include industry fixed effects and cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Useful Life and Change in Salary

Dependent Variable: Δ*Salary*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.289**	-0.297*	-0.384**	-0.846***	-1.334***	-1.720***
	(-2.63)	(-1.89)	(-2.61)	(-3.56)	(-5.54)	(-6.03)
Observations	4,119	3,832	3,443	2,966	2,703	2,409
Adjusted R^2	0.010	0.014	0.017	0.044	0.061	0.091
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Panel B. Useful Life and Change in Salary by Seniority

Dependent Variable: Δ*Salary*	(1)	(2)	(3)	(4)	(5)	(6)
Seniority 1 - *ln(UsefulLife)*	-0.117	-0.166	-0.233*	-0.540**	-0.986***	-1.366***
	(-1.12)	(-1.30)	(-2.01)	(-2.79)	(-3.88)	(-3.74)
Seniority 2 - *ln(UsefulLife)*	-0.241	-0.284	-0.329	-0.667**	-1.098**	-1.541**
	(-1.18)	(-1.04)	(-1.16)	(-2.14)	(-2.80)	(-2.60)
Seniority 3 - *ln(UsefulLife)*	-0.174	-0.172	-0.223	-0.531	-0.872	-1.202
	(-0.75)	(-0.54)	(-0.67)	(-1.36)	(-1.54)	(-1.57)
Seniority 4 - *ln(UsefulLife)*	-0.188	-0.189	-0.263	-0.617***	-1.031***	-1.389***
	(-1.00)	(-0.79)	(-1.15)	(-3.28)	(-4.34)	(-3.53)
Seniority 5 - *ln(UsefulLife)*	-0.342*	-0.358	-0.471*	-0.973***	-1.613***	-2.310***
	(-1.84)	(-1.33)	(-1.75)	(-2.94)	(-3.54)	(-3.31)
Seniority 6 - *ln(UsefulLife)*	-0.255	-0.118	-0.0790	-0.220	-0.529**	-0.735*
	(-1.24)	(-0.47)	(-0.40)	(-1.33)	(-2.10)	(-1.77)
Seniority 7 - *ln(UsefulLife)*	0.0815	0.110	0.154	0.0705	0.0399	0.146
	(0.69)	(0.70)	(0.72)	(0.25)	(0.16)	(0.67)
Adjusted R^2	0.013	0.022	0.025	0.023	0.024	0.025
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Table 11: Labor Share

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in firm-level labor share on *ln(UsefulLife)*. The unit of observation is at the acquirer-year level. *Weight* is the ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition. The unit of observation is at the acquirer-year level. The explanatory variables are the log of useful life of customer data (*ln(UsefulLife)*), its weight (*Weight*), and their multiplicative interaction (*ln(UsefulLife)* × *Weight*) The dependent variable, Δ*LaborShare*, is defined as the log difference in labor share between year t-1 and future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in labor share. In Panel A, we include industry fixed effects. In Panel B, we include industry and year fixed effects. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Industry Fixed Effects

Dependent Variable: Δ*LaborShare*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	-0.651	-0.755	-1.137*	-1.905***	-1.582*	-1.175
	(-1.32)	(-0.98)	(-1.78)	(-3.77)	(-2.00)	(-1.04)
ln(UsefulLife)	-1.819	-1.786	-1.225	-0.917	-0.577	-1.841
	(-1.12)	(-0.79)	(-0.41)	(-0.31)	(-0.16)	(-0.52)
Weight	3.984***	4.229**	5.204***	7.075***	6.212***	4.761*
	(3.67)	(2.33)	(3.16)	(5.43)	(3.21)	(1.75)
Observations	3,451	3,030	2,569	2,100	1,831	1,555
Adjusted R^2	0.064	0.048	0.060	0.070	0.072	0.066
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Panel B: Industry and Year Fixed Effects

Dependent Variable: Δ*LaborShare*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	-0.704	-0.762	-0.957	-1.794***	-1.411*	-0.945
	(-1.63)	(-1.11)	(-1.47)	(-3.51)	(-1.86)	(-0.85)
ln(UsefulLife)	-1.294	-1.944	-2.055	-0.641	-0.417	-1.086
	(-0.77)	(-0.87)	(-0.67)	(-0.22)	(-0.12)	(-0.28)
Weight	4.078***	4.247**	4.887***	6.823***	5.799***	4.354
	(4.22)	(2.61)	(2.92)	(5.26)	(3.23)	(1.66)
Observations	3,451	3,030	2,569	2,100	1,831	1,555
Adjusted R^2	0.110	0.101	0.113	0.096	0.092	0.084
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Table 12: Innovation and Useful Life

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses *ln(UsefulLife)* on various measures of innovation. In Panels A and B, we include *ln(UsefulLife)*^{2} and values are expressed as percents. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. We include industry fixed effects and cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Firm Share of Granted Patents

Dependent Variable: *PctPatents*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	0.0610***	0.107**	0.151***	0.155**	0.334**	-0.617
	(3.07)	(2.67)	(3.75)	(2.67)	(4.54)	(-0.85)
ln(UsefulLife)^2	-0.0270***	-0.0446***	-0.0638***	-0.0763***	-0.128**	0.0823
	(-3.22)	(-3.17)	(-3.98)	(-3.98)	(-3.92)	(0.54)
Observations	979	517	303	187	112	79
Adjusted R^2	0.030	0.034	0.034	0.062	0.129	0.180
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Panel B. Firm Share of Citations

Dependent Variable: *PctCitations*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	0.0467***	0.0883**	0.146***	0.144**	0.370**	-0.495
	(3.05)	(2.90)	(3.63)	(2.92)	(5.03)	(-0.61)
ln(UsefulLife)^2	-0.0256***	-0.0427***	-0.0639***	-0.0759***	-0.138**	0.0553
	(-3.87)	(-3.25)	(-3.86)	(-3.83)	(-4.64)	(0.32)
Observations	979	517	303	187	112	79
Adjusted R^2	0.062	0.048	0.031	0.060	0.120	0.152
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Panel C. Innovation Productivity of Employees

Dependent Variable: *CitePerInnovator*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.102***	-0.0940***	-0.0652	-0.125***	-0.0667*	-0.0546
	(-3.42)	(-6.82)	(-2.33)	(-7.09)	(-2.47)	(-1.45)
Observations	493	263	156	102	61	41
Adjusted R^2	-0.009	0.031	0.043	0.114	0.038	0.009
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

Table 13: Investment in Innovation and Useful Life

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in R&D investment, *PctR&D*, on *ln(UsefulLife)*. The unit of observation is at the acquirer-year level. *Weight* is the ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition. The unit of observation is at the acquirer-year level. The explanatory variables are the log of useful life of customer data (*ln(UsefulLife)*), its weight (*Weight*), and their multiplicative interaction (*ln(UsefulLife)* × *Weight*) The dependent variable, Δ*PctR&D*, is defined as the log difference in R&D investment between year t-1 and future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in R&D investment. In both Panel A, we include industry fixed effects. In Panel B, we include industry and year fixed effects. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Year Fixed Effects

Dependent Variable: Δ*PctR&D*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	-1.040	-7.134*	-15.43*	-28.07*	-29.38	-20.15
	(-0.55)	(-2.05)	(-2.15)	(-2.42)	(-1.19)	(-0.76)
Weight	-1.146	13.47	34.46	68.42*	70.97	54.86
	(-0.20)	(1.77)	(1.80)	(2.43)	(1.33)	(0.93)
ln(UsefulLife)	91.98***	95.62***	99.14***	114.6***	110.0	101.3
	(6.07)	(6.28)	(7.42)	(4.63)	(1.91)	(1.49)
Observations	389	227	139	87	59	40
Adjusted R^2	0.399	0.407	0.435	0.369	0.243	0.225
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Panel B. Year and Industry Fixed Effects

Dependent Variable: Δ*PctR&D*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife) × *Weight*	-1.787	-8.203*	-16.07**	-25.88***	-29.63	-21.40
	(-0.69)	(-1.99)	(-2.94)	(-5.69)	(-2.08)	(-1.11)
Weight	0.679	16.31	37.08*	64.72***	73.71*	66.46
	(0.09)	(1.66)	(2.65)	(6.95)	(2.83)	(1.85)
ln(UsefulLife)	95.46***	104.9***	111.9***	128.2***	125.3*	103.7
	(5.73)	(7.03)	(6.24)	(6.50)	(2.57)	(1.39)
Observations	389	227	139	87	59	39
Adjusted R^2	0.395	0.408	0.435	0.443	0.258	0.223
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]

Online Appendix for "Rising Customer Durability, Falling Business Dynamism"

This appendix contains additional analyses and details referenced in our paper and is organized as follows:

- Sample Selection in OA.A.
- An Explanation of Useful Life Estimates in OA.B.
- Additional Details of the Model in OA.C.
- Useful Life by Subsector (3-digit NAICS) in OA.D.
- Customer-Relationship Related Key Word List in OA.E.
- Acquirer-Year Summary Statistics in OA.F.
- Forward-Looking Gross Margin and Useful Life of Customer Data in OA.G.
- Robustness for Weighted Regressions in OA.H.
- Forward-Looking and Current Industry Concentration in OA.I.
- Entry Rates and HHI in OA.J.
- Robustness for Reallocation Rates in OA.K.

OA.A Sample Selection & Disclosures

Notes: Panel A presents the selection of our final sample. Panel B displays a sample Purchase Price Allocations (PPA) disclosure obtained from a 10-K filing of the acquirer. Panel C displays the useful life estimates for the intangible assets acquired.

Panel A. Sample Selection

Total deals between 2002-2024	20,991
Deals with acquirer data available in Compustat	19,812
Deals with customer relationships	10,776
Final sample: Deals with non-missing useful life of customer relationships	9,444

Panel B. Sample PPA

in millions		Preliminary Fair Value
Cash and cash equivalents	$	161
Receivables		1,831
Merchandise inventories		1,988
Property and equipment		789
Goodwill		11,006
Intangible assets		5,780
Other current and non-current assets		744
Total assets acquired	$	22,299
Accounts payable	$	1,791
Other current liabilities		584
Deferred tax liabilities (1)		1,114
Other long-term liabilities		782
Total liabilities assumed	$	4,271
Net assets acquired	$	18,028

Panel C. Sample Useful Life Disclosure

The acquisition date fair values of identifiable intangible assets were determined by using certain estimates and assumptions that are not observable in the market. The Company used the multi-period excess earnings method to determine the estimated acquisition date fair values of the customer relationships intangible assets. The significant assumptions used to estimate the fair values of customer relationships included forecasted revenues, expected customer attrition rates, and the discount rate applied. Determining the useful life of an intangible asset also requires judgment, as different types of intangible assets will have different useful lives.

The estimated fair values and estimated useful lives of identifiable intangible assets are as follows:

in millions	Weighted Average Useful Life (Years)		Fair Value
Customer relationships	20	$	5,400
Trade names	5		380
Total identifiable intangible assets		$	5,780

OA.B An Explanation of Useful Life Estimates

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

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

Although companies are required to disclose useful life estimates for intangible assets acquired through business combinations, they do not provide these estimates for internally developed intangible assets. This discrepancy in reporting stems from the accounting standards for internally generated intangible capital. Investments in the development of such capital are recorded as expenses on a company's financial statements during the period they occur and, therefore, are not recognized as assets on the balance sheet. Consequently, there is no stock of internally generated intangible capital on the balance sheet to be depreciated. Thus, our data on the useful life of acquired intangible assets likely offer new insights into the economic life of acquirers' internally generated intangible capital as well.

OA.C Additional Details of the Model

Representative Household. A representative household derives utility from consumption according to the logarithmic specification:

$$U_t = \int_t^{\infty} e^{-\rho(s-t)} \ln C_s \, \mathrm{d}s, \tag{C.1}$$

where C_s denotes consumption at time s and $\rho > 0$ is the rate of time preference. The household supplies one unit of labor inelastically at each point in time and owns all firms in the economy. The household's budget constraint requires that consumption plus the accumulation of assets equal labor income plus returns on asset holdings:

$$C_t + \dot{A}_t = w_t + r_t A_t, \tag{C.2}$$

where w_t is the wage rate, r_t is the interest rate, and A_t is the household's asset holdings. In equilibrium, assets equal the total value of firms in the economy.

Follower Value Function. Consider a follower that is $m > 0$ steps behind. The follower earns zero operating profit but invests in R&D with the prospect of catching up. The normalized value satisfies:

$$\begin{aligned}\rho v_{-m} = \max_{x_{-m}} \Bigg\{ & 0 - \frac{\alpha x_{-m}^{\gamma}}{\gamma}\omega + (1-\delta)x_{-m}(v_{-(m-1)} - v_{-m}) \\ & + \delta x_{-m}(v_0 - v_{-m}) + x_m(v_{-(m+1)} - v_{-m}) + \tilde{x}_{-m}(0 - v_{-m}) \Bigg\}. \end{aligned} \tag{C.3}$$

Neck-and-Neck Value Function. Consider a firm in a neck-and-neck product line. By symmetry, both firms choose the same innovation rate x_0. The normalized value satisfies:

$$\rho v_0 = \max_{x_0} \left\{ \frac{\phi}{2} - \frac{\alpha x_0^{\gamma}}{\gamma}\omega + x_0(v_1 - v_0) + x_0(v_{-1} - v_0) + \tilde{x}_0 \left(\frac{1}{2} v_{-1} - v_0 \right) \right\}. \tag{C.4}$$

Entrant. Each period a potential entrant in product line j solves a static profit-maximization problem, choosing innovation intensity to maximize expected value of entry minus R&D costs. In an unleveled sector with gap $m > 0$, the entrant's problem is:

$$\max_{\tilde{x}_{-m}} \left\{ -\frac{\tilde{\alpha}\tilde{x}_{-m}^{\tilde{\gamma}}}{\tilde{\gamma}}\omega + \tilde{x}_{-m}\left[(1-\tilde{\delta})v_{-(m-1)} + \tilde{\delta} v_0 \right] \right\}. \tag{C.5}$$

In a neck-and-neck sector ($m = 0$), the entrant's problem is:

$$\max_{\tilde{x}_0} \left\{ -\frac{\tilde{\alpha}\tilde{x}_0^{\tilde{\gamma}}}{\tilde{\gamma}}\omega + \tilde{x}_0 \cdot v_1 \right\}. \tag{C.6}$$

The entrant's optimal innovation rates are therefore

$$\tilde{x}_{-m} = \left[\frac{(1-\tilde{\delta})v_{-(m-1)} + \tilde{\delta}v_0}{\tilde{\alpha}\omega} \right]^{\frac{1}{\tilde{\gamma}-1}}, \tag{C.7}$$

and

$$\tilde{x}_0 = \left[\frac{v_1}{\tilde{\alpha}\omega} \right]^{\frac{1}{\tilde{\gamma}-1}}. \tag{C.8}$$

Production labor. In a product line with gap $m > 0$, only the leader produces:

$$\ell_L(m) = \frac{(1-\phi)Y}{\omega\lambda^m}. \tag{C.9}$$

In a neck-and-neck product line, each firm charges $p = w/[q(1-\phi)]$ and produces half the output, so total production labor is $(1-\phi)/\omega$. Aggregate production labor is:

$$L^{prod} = \sum_{m=1}^{\bar{m}} \mu_m \frac{(1-\phi)}{\omega\lambda^m} + \mu_0 \frac{(1-\phi)}{\omega} = \frac{(1-\phi)}{\omega}\left[\mu_0 + \sum_{m=1}^{\bar{m}} \mu_m \lambda^{-m} \right]. \tag{C.10}$$

R&D Labor. Aggregate R&D labor is given by

$$L^{R\&D} = \mu_0 \left[2\frac{\alpha}{\gamma}x_0^{\gamma} + \frac{\tilde{\alpha}}{\tilde{\gamma}}\tilde{x}_0^{\tilde{\gamma}} \right] + \sum_{m=1}^{\bar{m}} \mu_m \left[\frac{\alpha}{\gamma}x_m^{\gamma} + \frac{\alpha}{\gamma}x_{-m}^{\gamma} + \frac{\tilde{\alpha}}{\tilde{\gamma}}\tilde{x}_{-m}^{\tilde{\gamma}} \right]. \tag{C.11}$$

Distribution of Technology Gaps. Let μ_m denote the fraction of product lines in which the leader is m steps ahead, for $m \in \{0, 1, \ldots, \bar{m}\}$. The stationary distribution satisfies

$$\sum_{m=0}^{\bar{m}} \mu_m = 1. \tag{C.12}$$

For $m = 0$,

$$\dot{\mu}_0 = (x_{-1} + \tilde{x}_{-1})\,\mu_1 + \sum_{m=2}^{\bar{m}} \left[\delta x_{-m} + \tilde{\delta}\tilde{x}_{-m} \right] \mu_m - (2x_0 + \tilde{x}_0)\,\mu_0. \tag{C.13}$$

For $m = 1$,

$$\dot{\mu}_1 = (2x_0 + \tilde{x}_0)\,\mu_0 + \left[(1-\delta)x_{-2} + (1-\tilde{\delta})\tilde{x}_{-2}\right]\mu_2 - (x_1 + x_{-1} + \tilde{x}_{-1})\,\mu_1. \tag{C.14}$$

For interior states $2 \le m \le \bar{m} - 1$,

$$\dot{\mu}_m = x_{m-1}\mu_{m-1} + \left[(1-\delta)x_{-(m+1)} + (1-\tilde{\delta})\tilde{x}_{-(m+1)}\right]\mu_{m+1} - (x_m + x_{-m} + \tilde{x}_{-m})\,\mu_m. \tag{C.15}$$

At the upper boundary, we assume that additional leader innovation does not change the state once the gap reaches $\bar{m}$. Hence

$$\dot{\mu}_{\bar{m}} = x_{\bar{m}-1}\mu_{\bar{m}-1} - (x_{-\bar{m}} + \tilde{x}_{-\bar{m}})\,\mu_{\bar{m}}. \tag{C.16}$$

Aggregate Growth. Aggregate productivity growth is given by

$$g = \ln\lambda\left[2\mu_0 x_0 + \mu_0\tilde{x}_0 + \sum_{m=1}^{\bar{m}}\mu_m x_m\right]. \tag{C.17}$$

Only neck-and-neck innovation, neck-and-neck entry, and leader innovation in unleveled sectors enter directly because these are the events that raise the productivity of the active producer in a product line. By contrast, follower innovation and entry in unleveled sectors alter the identity or proximity of challengers without directly increasing the productivity of the current leader.

Definition of Equilibrium A dynamic general equilibrium consists of sequences of prices, quantities, innovation rates, and distributions such that:

1. The final good producer maximizes profits.
2. Technology leaders set profit-maximizing prices given customer durability.
3. Incumbent firms choose innovation rates to maximize firm value.
4. Potential entrants choose innovation rates to maximize expected profits.
5. The labor market clears.
6. The household's Euler equation is satisfied.
7. The distribution of technology gaps evolves consistently with innovation rates.

OA.D Useful Life by Subsector

Notes: This table reports the distribution of customer useful life by industry, defined by three-digit NAICS codes. For publishing industries, we differentiate between software publishing and traditional publishing by their four-digit NAICS equivalents.

NAICS	Industry	Mean	N	% Sample	SD	p10	p25	p50	p75	p90	Mode
334	Computer & Electronic Product Manufacturing	8.19	1,162	12.30 %	4.38	3	5	7	10	15	10
513	Publishing Industries	7.52	818	8.66 %	4.21	3	5	6.5	10	13.5	5
	5132: Software Publishers	7.35	571	6.05 %	3.84	3	5	6.5	10	12.5	5
	5131: Newspaper, Periodical, Book & Directory Publishers	7.92	247	2.62 %	4.95	3	4.4	7	10	15	5
541	Professional, Scientific & Technical Services	8.40	776	8.22 %	4.39	3	5	7	10	15	10
518	Cloud, Data Processing & Web Hosting	8.60	605	6.41 %	4.05	3	5	8.5	11	15	5
325	Chemical Manufacturing	12.52	448	4.74 %	5.11	5	10	12.5	15	20	10
333	Machinery Manufacturing	11.54	445	4.71 %	5.02	5	8	10	15	19	10
524	Insurance Carriers & Related Activities	10.85	405	4.29 %	4.40	7	8.5	9	14	16	9
339	Miscellaneous Manufacturing	11.45	320	3.39 %	4.91	5	8	11	15	19.9	10
423	Merchant Wholesalers, Durable Goods	11.18	290	3.07 %	4.81	5.8	8	10	14.6	17	10
523	Securities & Financial Investments	10.39	272	2.88 %	5.73	3	6	10	14	18	9
336	Transportation Equipment Manufacturing	12.45	258	2.73 %	5.19	6	9	12	15	20	10
519	Web Search Portals, Libraries, Archives & Other Information Services	7.19	236	2.50 %	3.96	3	4.635	6.7	9	13	5
332	Fabricated Metal Product Manufacturing	14.01	218	2.31 %	4.72	8	11	14	17	20	10
517	Telecommunications	7.48	193	2.04 %	4.11	4	5	6	10	14	5
424	Merchant Wholesalers, Nondurable Goods	10.90	169	1.79 %	4.70	5	8	10	14	17.5	10
335	Electrical Equipment, Appliance & Component Manufacturing	11.73	147	1.56 %	5.24	5	8	10.5	15	19.5	10
322	Paper Manufacturing	14.27	105	1.11 %	5.58	8	10.5	14.8	17	20	10
331	Primary Metal Manufacturing	13.59	80	0.85 %	5.03	7	10	13.5	15.5	20	10
323	Printing & Related Support Activities	9.93	76	0.80 %	5.34	4	6	8	14.2	18	10
326	Plastics & Rubber Products Manufacturing	11.71	75	0.79 %	4.50	6	8.5	11	15	18	10
516	Broadcasting & Content Providers	6.89	49	0.52 %	5.03	1	4	5	10	14.2	5
321	Wood Product Manufacturing	10.04	34	0.36 %	3.37	5	8.5	10	13	14.4	10
327	Nonmetallic Mineral Product Manufacturing	10.13	32	0.34 %	4.66	4	7.8	10	13.5	15	10
324	Petroleum & Coal Products Manufacturing	14.66	27	0.29 %	6.70	4	12	15	20	20	10
337	Furniture & Related Product Manufacturing	11.54	26	0.28 %	4.90	5	9	10.5	15	20	10
425	Wholesale Trade Agents & Brokers	10.57	19	0.20 %	6.33	5	5	9	12	20	10
525	Funds, Trusts & Other Financial Vehicles	7.92	15	0.16 %	5.68	.5	4	7.98	10	19	9
512	Motion Picture & Sound Recording Industries	7.00	13	0.14 %	4.32	2.67	4.165	5	10	13.2	5
.	Total	9.79	7,313	72.55 %	5.05	4	6	9.3	13	16.4	10

OA.E Customer-Relationship Related Key Word List

Durability language
`(durability)`
customer continuity plans
relationship stability
long-term value
sticky revenue
recurring relationships
customer continuity
durable customer relationships
relationship durability
durable revenue
stable customer relationships

Customer advocacy and loyalty signals
`(feedback_loyal)`
customer references
case studies
customer referrals
rewards program
customer incentives
reference customers
retention incentives
referral program
customer testimonials
loyalty programs

Switching costs & customer lock-in
`(lock_in_switch_costs)`
customer integration
workflow automation
network effect
switching difficulties
customer dependence
mission-critical services
migration costs
critical services
ecosystem lock-in
network effects
high adoption barriers
integration costs
core platform
change management
process automation
implementation costs
customer reliance
system of record
revenue retention
switching complexity
switching cost indicators
platform dependence
embedded platform
business process integration
retention of revenue
operational reliance
essential services
core systems
system of engagement
critical systems
customer stickiness indicators
platform ecosystem

Repeat purchasing and reorder behavior
`(repeat_reorder)`
reorders
returning customers
repeat orders
repeat customers
repeat purchases
repeat business
reorder rate

Retention and churn metrics
`(retention_churn)`
attrition rate
subscription renewals
contract renewals
renewal rate
NRR
net revenue retention
customer retention
reduced churn
renewal base
renewal backlog
renewal pipeline
dollar-based retention
customer loyalty
low churn
customer attrition
churn
renewals
churn rate
retention rate
dollar-based net retention
gross retention

Subscriber-base language
`(subscriptions)`
subscriber churn
subscriber base
subscriber growth
subscription base
subscriber retention
active subscribers

Stickiness Language
`(switching_costs_sticky)`
switching risk
customer stickiness
embedded in operations
mission-critical
switching barriers
workflow integration
integrated platform
embedded in workflows
sticky customers
integration with customer systems
essential to operations
mission critical
integral to operations
high switching costs
switching costs
critical to operations
embedded solutions
deep integration
integrated solution

OA.F Acquirer-Year Summary Statistics

Notes: This table presents descriptive statistics for our collapsed sample of mergers and acquisitions. Panel A reports the distribution statistics across 7,888 acquirer-years with a reported useful life. *UsefulLife* is reported in years. Panel B presents descriptive statistics for our tested outcome variables observed in the t+1 time period, where t denotes the acquisition year.

Panel A. Useful Life by Industry

NAICS	Industry Description	Mean	N	% Sample	SD	p10	p25	p50	p75	p90	Mode
33	Manufacturing	10.62	2,135	27.09 %	5.21	4.962	6.597	10	15	18	10
51	Information	7.74	1,467	18.61 %	4.21	3	5	7	10	14	5
52	Finance and Insurance	10.48	973	12.34 %	4.64	5	7.5	10	13	16	10
32	Manufacturing	12.48	618	7.84 %	5.32	5	9	12.08	15	20	15
54	Professional, Scientific, and Technical Services	8.54	583	7.40 %	4.29	3.6	5.5	7.4	10.31	15	10
42	Wholesale Trade	11.09	383	4.86 %	4.73	5	8	10	14.5	18	10
56	Administrative, Support, Waste, and Remediation Services	10.69	273	3.46 %	4.93	5	7	10	14	16	10
31	Manufacturing	13.37	234	2.97 %	5.37	7	10	13.88	16	20	15
53	Real Estate and Rental and Leasing	10.00	217	2.75 %	6.86	2	6	8.488	13	18.46	7
48	Transportation and Warehousing	12.45	162	2.06 %	6.29	5.5	8	11.5	15	20	15
62	Health Care and Social Assistance	10.54	133	1.69 %	5.01	4.5	6.8	10	13.5	18.5	10
21	Mining, Quarrying, and Oil and Gas Extraction	13.42	113	1.43 %	8.74	4	7.3	12.17	17	25	15
44	Retail Trade	9.55	106	1.34 %	4.82	4	5.5	9	11.6	15.5	10
23	Construction	10.86	106	1.34 %	4.44	5.913	8	10	14.03	15	10
45	Retail Trade	9.20	90	1.14 %	5.67	3	4.956	7	13	18	5
22	Utilities	13.59	64	0.81 %	8.70	4.362	9	12	15	26	11
71	Arts, Entertainment, and Recreation	6.95	62	0.79 %	4.15	2.5	4	6	9.478	14	6
61	Educational Services	5.01	41	0.52 %	3.27	2.182	3	4	5.8	10	3
72	Accommodation and Food Services	10.03	38	0.48 %	5.14	4	5	9.75	14.8	15	15
81	Other Services (except Public Administration)	7.40	27	0.34 %	3.53	3	5	7	10	12	10
11	Agriculture, Forestry, Fishing and Hunting	12.55	27	0.34 %	4.92	7	9.5	11.5	16	20	20
99	Unclassifiable Establishments	8.94	22	0.28 %	5.25	3	6.8	8	11	18.88	8
49	Transportation and Warehousing	12.53	8	0.10 %	2.31	8.933	11	12.25	14.9	15	15
.	Total	10.15	7,888	100.00 %	5.30	4	6	10	13.6	17	10

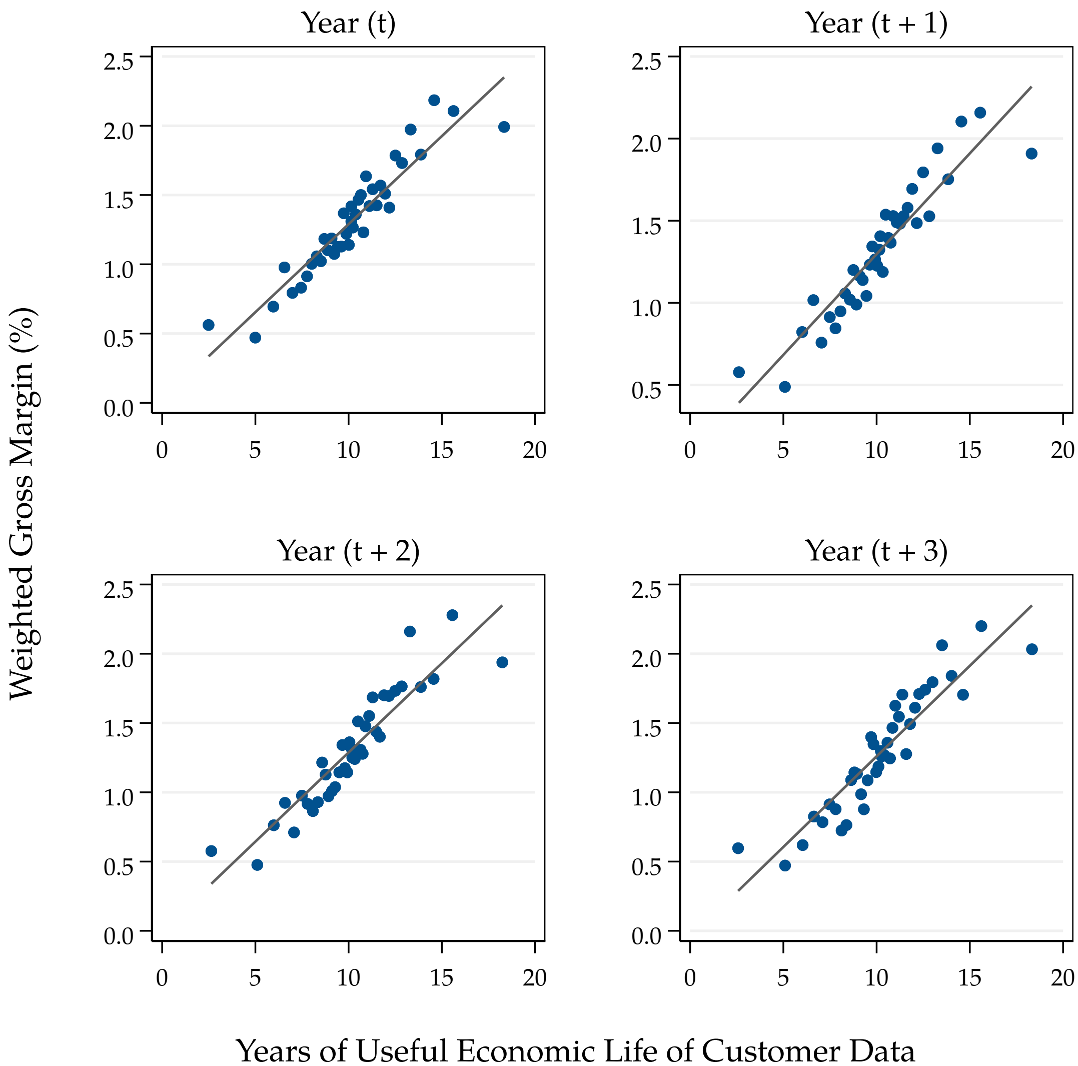
OA.F Acquirer-Year Summary Statistics (continued)

Panel B. Distribution of Dependent Variables

Dependent Variable	N	Mean	SD	p10	p25	p50	p75	p90
GrossMargin	5,856	0.44	0.22	0.17	0.27	0.41	0.61	0.74
EBITMargin	6,303	-0.13	4.61	-0.15	0.01	0.08	0.14	0.22
HHI	2,908	533.87	529.83	62.44	158.74	375.85	722.65	1215.52
$ReallocationRate_{Compustat}$	5,741	26.76	26.51	5.11	10.53	20.78	32.99	52.21
$ReallocationRate_{Revelio}$	4,119	8.49	5.43	3.28	5.04	7.49	10.17	15.07
$ReallocationRate_{Census}$	6,126	6.77	6.75	0.96	2.31	5.01	9.14	14.66
$ExcessReallocRate_{Census}$	6,126	21.71	8.16	12.55	15.43	20.24	26.57	33.35
Salary (Thousands)	4,346	76.09	17.28	56.10	63.47	74.72	85.60	100.57
EntryRate	6,122	9.61	4.86	4.84	5.87	8.68	12.35	15.79
$PctEmp_{Age \leq 5}$	6,126	8.51	6.17	2.73	4.06	6.53	11.70	17.35
PctPatents	971	0.08	0.32	0.00	0.00	0.01	0.03	0.14
PctCitations	971	0.09	0.33	0.00	0.00	0.01	0.03	0.16
PctR&D	742	9.94	10.63	0.77	1.94	6.59	13.55	24.68
CitePerInnovator	496	0.19	0.74	0.00	0.00	0.04	0.16	0.45

OA.G Forward-Looking Gross Margin and Useful Life of Customer Data

Notes: These figures plot the relationship between the gross margin of the acquiring firm and the estimated useful life of customer data from acquisition year, t, to t+3. Observations are aggregated to the acquirer-year level. We weight the gross margin by the ratio of the fair value of customer data to the value of the acquiring firm's assets in the year of the acquisition and include acquirer fixed-effects. We use Binscatter to generate the figures. As such, the dots represent the average outcome for a 'bin,' where bins are created automatically by the software program, and include a "best fit" line in black.



OA.H Robustness for Weighted Regressions

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses changes in gross margin, EBIT margin, and profit share on useful life and its weight. All variables are described in Appendix A. In columns (1) through (3), we include industry fixed effects. In columns (4) through (6), we include industry and year fixed effects. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Gross Margin

Dependent Variable: $\Delta GrossMargin$	(1)	(2)	(3)	(4)	(5)	(6)
UsefulLife × *Weight*	3.134**	4.292*	3.121**	3.074**	4.091*	2.985**
	(2.63)	(2.06)	(2.45)	(2.67)	(1.95)	(2.27)
Weight	-35.43*	-54.05*	-27.35	-34.66*	-51.93	-26.96
	(-1.88)	(-1.83)	(-1.60)	(-1.86)	(-1.71)	(-1.49)
UsefulLife	-0.0346	-0.0630	-0.0978	-0.0403	-0.0770	-0.131
	(-0.61)	(-0.77)	(-0.94)	(-0.70)	(-0.89)	(-1.18)
Observations	5,585	4,953	4,289	5,585	4,953	4,289
Adjusted R^2	0.004	0.004	0.008	0.005	0.006	0.010
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel B. Ebit Margin

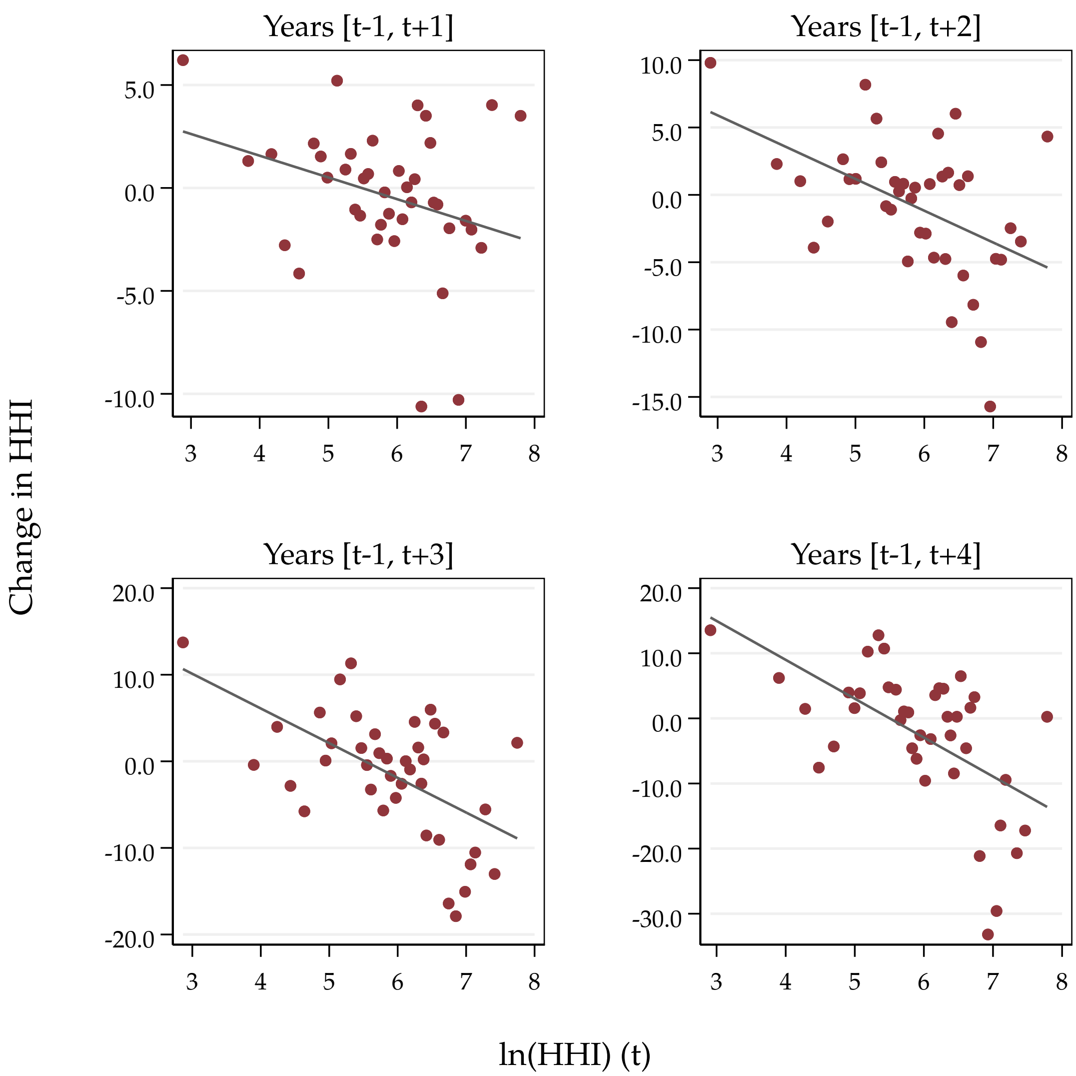
Dependent Variable: $\Delta EbitMargin$	(1)	(2)	(3)	(4)	(5)	(6)
UsefulLife × *Weight*	5.061	7.339	14.59***	4.538	6.675	13.73***
	(0.86)	(1.34)	(3.85)	(0.78)	(1.24)	(3.65)
Weight	-148.9	-182.7**	-298.6***	-142.4	-171.2**	-290.6***
	(-1.64)	(-2.45)	(-4.71)	(-1.57)	(-2.35)	(-4.68)
UsefulLife	0.404	0.323	0.242	0.433*	0.345	0.231
	(1.66)	(1.22)	(0.85)	(1.83)	(1.21)	(0.76)
Observations	4,508	4,005	3,513	4,508	4,005	3,513
Adjusted R^2	0.006	0.006	0.013	0.017	0.012	0.019
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

Panel C. Profit Margin

Dependent Variable: $\Delta ProfitShare$	(1)	(2)	(3)	(4)	(5)	(6)
UsefulLife × *Weight*	3.480	4.025	13.40**	2.880	6.325	11.28**
	(0.58)	(0.72)	(2.59)	(0.50)	(1.16)	(2.81)
Weight	108.3	109.3	-15.19	112.1	75.27	7.349
	(1.22)	(1.28)	(-0.14)	(1.31)	(0.96)	(0.08)
UsefulLife	0.287	0.344	0.0912	0.429	0.405	0.220
	(0.90)	(1.28)	(0.22)	(1.50)	(1.46)	(0.68)
Observations	4,506	4,003	3,511	4,506	4,003	3,511
Adjusted R^2	0.008	0.014	0.011	0.040	0.044	0.050
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	Y	Y	Y
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]

OA.I Forward-Looking and Current Industry Concentration

Notes: These figures plot the relationship between the change in Herfindahl–Hirschman index (HHI) and the HHI value observed in the acquiring firm's industry in acquisition year, t. Change in HHI is the log difference in the HHI of the acquiring firm's industry between years t-1 and years t+1 through t+4. We use Binscatter to generate the figures. As such, the dots represent the average outcome for a 'bin,' where bins are created automatically by the software program, and include a "best fit" line in black.



OA.J Entry Rates and HHI

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses the firm entry rate, *EntryRate*, on *ln(HHI)*. *EntryRate* is reported by Census BDS by industry for future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. In Panel A, we include industry fixed effects. In Panel B, we include industry and year fixed effects. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in firm entry rates. We cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Industry Fixed Effects						
Dependent Variable: *EntryRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI)	0.0782	0.148	0.194	0.162	0.159	0.183
	(0.43)	(0.99)	(1.38)	(0.97)	(1.05)	(1.22)
Observations	3,005	2,734	2,420	2,244	2,040	1,843
Adjusted R^2	0.478	0.442	0.415	0.443	0.408	0.327
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6
Panel B. Industry and Year Fixed Effects						
Dependent Variable: *EntryRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(HHI)	0.0530	0.138	0.192	0.150	0.155	0.190
	(0.30)	(0.86)	(1.23)	(0.80)	(0.93)	(1.13)
Observations	3,005	2,734	2,420	2,244	2,040	1,843
Adjusted R^2	0.514	0.480	0.439	0.462	0.435	0.354
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	Y	Y	Y	Y	Y	Y
Time Period	t+1	t+2	t+3	t+4	t+5	t+6

OA.K Robustness for Reallocation Rates

Notes: This table presents results from an ordinary least-squares (OLS) model that regresses job reallocation rates on *ln(UsefulLife)*. In Panel A, we compute *ReallocationRate* using Census BDS reported employee counts between year t-1 and future years t+1 through t+6, where t denotes the acquisition year. All variables are described in Appendix A. The unit of observation is at the acquirer-year level. In Panel B, *ExcessReallocRate* is the Census BDS reported excess reallocation rate between a given year and the year prior, which measures the rate of job reallocation above that needed to accommodate the net job creation in the industry. Values are expressed as percent changes, so coefficients can be interpreted as percentage point changes in the reallocation rate. We include industry fixed effects and cluster standard errors at the industry level. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Estimated Job Reallocation Over Time						
Dependent Variable: *ReallocationRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-1.172***	-1.528***	-2.068**	-2.580**	-3.155**	-3.641*
	(-4.30)	(-3.74)	(-2.73)	(-2.47)	(-2.12)	(-1.97)
Observations	6,126	5,740	5,249	4,966	4,641	4,322
Adjusted R^2	0.078	0.084	0.083	0.095	0.106	0.116
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]
Panel B. Yearly Excess Job Reallocation						
Dependent Variable: *ExcessReallocRate*	(1)	(2)	(3)	(4)	(5)	(6)
ln(UsefulLife)	-0.657***	-0.969***	-0.870***	-0.827***	-0.784**	-0.725**
	(-3.03)	(-4.37)	(-3.10)	(-3.17)	(-2.50)	(-2.58)
Observations	6,126	5,740	5,249	4,966	4,641	4,322
Adjusted R^2	0.536	0.545	0.542	0.544	0.551	0.540
Industry F/E	Y	Y	Y	Y	Y	Y
Year F/E	N	N	N	N	N	N
Time Period	t+1	t+2	t+3	t+4	t+5	t+6