Obsolete Firms

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When innovation creates winners and economic gains, it also creates losers and leads to losses by rendering existing technologies obsolete. This obsolescence is central in endogenous growth theories and models of creative destruction, yet empirical analysis on it is scarce. This paper proposes a new measure of technology obsolescence at the firm-year level using detailed annual patent and citation data. Armed with this measure, we perform three sets of tests. First, for firms, technology obsolescence foreshadows substantially lower growth, productivity, and reallocation of capital. This finding applies mainly for obsolescence of core innovation and embodied innovation; and is stronger when product markets are competitive. Second, a measure that aggregates technology obsolescence can explain a substantial fraction of economic growth, fluctuations, and productivity. Last, for technology obsolescence strongly predicts stock returns of firms, while a long-short portfolio strategy earns an abnormal return of 7–8% annually. Importantly, the measure contains additional and largely independent information relative to existing measures of new innovation. (*JEL*: O3, O4)

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The Schumpeterian narrative of creative destruction has two pillars. The well-studied one is the innovation process—*creative* innovation is produced and adopted, leading to the expansion of product variety, increase of productivity, and eventually the growth of the economy. The state-of-the-art work combines patent information with stock-market data upon patent approval (Kogan, Papanikolaou, Seru, and Stoffman, 2017, *hereafter* KPSS) or text-based method (Kelly, Papanikolaou, Seru, and Taddy, 2021) and achieves remarkable success in showing how the arrival of innovation is associated with firm growth, active resource reallocation, and economic prosperity.

This paper focuses on the *destruction* pillar, which is less understood. As innovation creates winners and economic gains, it also creates losers and renders value losses—as some win, some are left behind (Aghion and Howitt, 1992; Kogan, Papanikolaou, and Stoffman, 2020). This destruction mechanism functions through technology obsolescence: existing products, physical capital, human capital and labor skills become less valuable when technology progresses. Why should we care about those left-behind? In endogenous growth theory, technology obsolescence drives the heterogeneity in cross-sectional profitability and productivity of firms, and creates the momentum for the reallocation of capital.[1] At the aggregate level, the economy bears the cost of restructuring thus innovation is costly—could affect the overall benefit of innovation.[2] Beyond the ex post cost associated with tech obs, the risks of experiencing so drives asset prices and thus the cost of financing innovation, human capital choice, and income equality.[3] More broadly, the well-being of the left-behind is also crucial in addressing broad social issues and overall welfare.[4]

Despite the conceptual importance, predictions of these models featuring technology obsolescence prove challenging to test, mainly because of the scarcity of directly observable of technology obsolescence at granular levels. An ideal measure should capture the level of technology obsolescence that each firm experiences in its existing technology stock at each point in time. Preferably, the measure should reflect the combined technological disruption from various sources: scientific discoveries, industry competitors' research and development (R&D), emergence of new markets and industries, or sometimes cannibalization by a firm's own successful innovation through variety expansion or quality upgrade. This paper aims to fill this gap by constructing a such a measure and

[1]See, for example, Grossman and Helpman (1991), Aghion and Howitt (1992), Klette and Kortum (2004), Lentz and Mortensen (2008), and Aghion, Akcigit, and Howitt (2014).

[2]See, for example, Caballero and Hammour (1996), Acemoglu et al. (2018), Akcigit and Kerr (2018), and Garcia-Macia, Hsieh, and Klenow (2019).

[3]Kogan and Papanikolaou (2019) provide a recent survey of the literature that introduces technological innovation into asset pricing. For some recent papers in this area, see Pástor and Veronesi (2009), Papanikolaou (2011), Gârleanu, Panageas, and Yu (2012), Ai, Croce, and Li (2013), Eisfeldt and Papanikolaou (2013), Kogan and Papanikolaou (2014), Gârleanu and Panageas (2018), Kogan, Papanikolaou, and Stoffman (2020), and Kogan et al. (2020).

[4]See Aghion, Akcigit, Deaton, and Roulet (2016) for a recent example.

proving its usefulness in testing comprehensive theoretical predictions.

The first part of the paper proposes the measure, *Technology Obsolescence*, for each firm-year. The measure aims to quantify the relative movement of a firms' existing technology from the technology frontier, and a firm's technologies become obsolete if they move away from the frontier and become less useful in generating new innovation. The measure construction has three steps. First, we define a firm's technology base each year as all the patents that it ever cited in its own innovation up to that year. A close analogy is to capture a researcher's key knowledge base using all the papers and books cited in his or her research papers. In the second step, we establish that technologies become obsolete in the evolutionary process, and that this process can be captured using *annual* citations that each patent receives. Generally, patents receive fewer and fewer citations as the underlying technology ages (Caballero and Jaffe, 1993; Hall, Jaffe, and Trajtenberg, 2001). Finally, we construct technology obsolescence as the change rate of citations made to each firm's technology base over a certain time period.

Consider the following example for illustration. Imagine a firm owned 20 patents in its patent portfolio in year 2003. The technology base consists of the patents that those 20 patents cited—say there were 350 patents in this base. Assume this base received 1,000 total external citations by other patents in 2003. Assume, in 2005, this same base received 900 citations in scenario 1; and 1,100 citations in scenario 2. The obsolescence measure will be 10% in scenario 1 (comparing 900 with 1,000), and −10% in scenario 2 (comparing 1,100 with 1,000). The latter, with negative obsolescence, is a sign of staying at or approaching to the frontier. Intuitively, this is a share-shift style measure, capturing the obsolescence of a firm's technology base due to heterogeneous exposures to various innovation paths.

The measure presents an opportunity to examine the basic patterns of technology obsolescence. On average, a firm's technology portfolio "ages" by 4–7 percent annually. There are losers and winners from the technology evolution, with the winning 25 percentile of firms enjoying negative obsolescence, while the losing 25 percentile of firms' technology being disrupted by 15–25 percent annually. This measure succeeds in capturing variations across firms in the same SIC3 industry and year, as more than 60 percent of the variations are within-industry-year. This empirical features allows our analysis to control timing-varying industry trends, which closely resonate the endogenous growth models.

The measure has a few desirable properties. To begin, it can capture various sources of technology disruption—within-firm innovation that outdates a firm's own technology, industry competitor's technological breakthroughs, or innovation from outside the industry that could disrupt the market. In fact, we show that these three sources are all important in explaining the rise of technology obsolescence. Second, the measure is general enough to accommodate flexible variations in the construction. As will be used in testing detailed theoretical predictions below, the measure can be tailored to capture obsolescence of core vs. peripheral patents, embodied and disembodied patents, more scientifically general vs. narrow patents. The logic behind the measure can also be applied to any other innovation-producing entity (e.g., private firms, research institutes, researcher teams, etc.). At last, it builds on pure scientific information using only patent information from the United States Patent and Trademark Office (USPTO). It does not rely on any other firm-level accounting information, ex post capital reallocation data, product market classification, or stock market data.

Armed with the new measure, *Technology Obsolescence*, we perform three sets of tests on its implications—for firm growth and capital reallocation; for aggregate economic growth and fluctuations; and for asset prices.

Firm Growth and Productivity. First, we test the relation between technology obsolescence and heterogeneity in firm growth, productivity, and resource reallocation. An unambiguous prediction of endogenous growth theories is that firms' performance deteriorates when their technologies become obsolete. This could be due to competitors' business stealing, or cannibalization by a firm's own innovation that devalues the exist physical and human capital.

Firms experiencing larger obsolescence with their technologies witness a significant lower growth. Over a five year period, compared to firms in the same industry-year, a one standard deviation higher in obsolescence is associated with slower growth in profit (2.1 percentage point), output (2.5 percentage point), capital (4.5 percentage point), and employment (1.5 percentage point). The same one standard deviation increase in obsolescence is associated with a 1.1 percent point decrease of revenue-based total factor productivity (TFP), showing the potential to explain the widely dispersed firm productivity (Syverson, 2011). These results are estimated with industry-by-year fixed effects, effectively comparing firms within the same industry during the same time period.

Technology obsolescence and measure of new innovation provide complementary and largely independent information. When we simultaneously incorporate them in the same empirical design, the economic impact of technology obsolescence remains virtually the same and statistically robust. Stock market-based patent value, as a measure for new innovation, robustly relates to growth and allocation, and that citation-weighted patent counts are fragile when testing the implications for firm growth, consistent with KPSS. We also compare *Technology Obsolescence* with those measure technology disruptions using valuable patents by public industry competitors (i.e., "other firms' win is my loss").[5] When being introduced into the analysis together, the obsolescence measure remain economically sizable and statistically significant. This means that our measure successfully captures disruptive innovation that could happen outside the industry domain, such as those by firms in other industries, or in research institutions and foreign corporations, or even the firms' own innovation.

We also examine heterogeneities of the result across innovation types and product market conditions. Noticeably, consistent with the idea that core patents are more closely associated with firm value (Akcigit, Celik, and Greenwood, 2016), we find larger negative firm outcomes when obsolescence happens in core technology areas (say engine technology in an automaker) and milder or negligible when it happens in peripheral areas (say entertainment system of the same automaker). Furthermore, we test the idea that embodied innovation, such as those new product that will require adjustment of physical and human capital (Berndt, 1990), may generate more severe destruction (Gârleanu, Panageas, and Yu, 2012; Kogan, Papanikolaou, and Stoffman, 2020). We code product innovation following Bena and Simintzi (2019) and find that product innovation obsolescence is associated with greater destruction. In addition, our results are stronger in industries that are more competitive.

Aggregate Economic Growth and Fluctuation. In the second part of the paper, we aggregate from the firm-level analysis and assess the role of technology obsolescence in accounting for medium-run fluctuations in economic growth and TFP. New innovation drives growth, but the resulting technology obsolescence leads to value loss of the physical, human, and organizational capital embodying the obsolete technology (Caballero and Hammour, 1996). It is costly for obsolete firms to restructure to adapt to new innovation, if at all possible, giving rise to the costs associated with technology evolution (Caballero and Jaffe, 1993). The goal of this section is to quantify these costs. Understanding these cost can help us better account for the aggregate value of new innovation and design innovation policy (Garcia-Macia, Hsieh, and Klenow, 2019).

When doing a simple aggregation using our firm-level results and all the firms in our sample, we estimate that the annual value loss aggregates to an equivalence of roughly 8 to 14 percent of the total firm growth in profits, output, and capital stock. Interestingly, technology obsolescence can explain substantially higher proportion of (negative) labor growth, scoring roughly 25 to 41 percents depending on the time horizon. This high labor-obsolescence sensitivity is suggestive evidence in

[5]Two recent influential studies, Bloom, Schankerman, and Van Reenen (2013) (*hereafter* BSV) and KPSS, adopts this approach.

support of the literature that highlights the role of skill obsolescence in explaining labor market dynamics (Rosen, 1975; Acemoglu and Autor, 2011; Kogan et al., 2020).

To study the relation between technology obsolescence and growth at the economy level, we construct an obsolescence index that averages firm-level obsolescence measures weighted by firm size (total assets or size of the patent portfolio). Our obsolescence index is negatively related to aggregate growth in output and TFP. In particular, a one standard deviation increase in our index is associated with a four percent lower in output and a one percent lower in measured TFP over a horizon of five years. Indeed, the size of destruction is substantial. Again, as in the first set of firm-level analysis, technology obsolescence adds additional information to the model compared to new technological breakthroughs.

Asset Prices and Cost of Financing Innovation. In the final set of analysis, we examine asset pricing implications of technology obsolescence. The central finding is: firms that have high realized technology obsolescence earn lower future returns than firms that have lower technology obsolescence. In a sorted-portfolio exercise, the average portfolio returns monotonically *decreases* with *Technology Obsolescence*. A spread portfolio that buys low-*Obsolescence* firm and shorts high-*Obsolescence* firms earns an value-weighted excess return of more than 7 percent annually. This spread portfolio has a Fama and French (2015) five-factor alpha of 57 basis points ($t = 3.931$) monthly, or 7.1 percent per year.

The alphas remain robust and sizable with alternative factor models, including the three-factor model (Fama and French, 1992), four-factor model (Carhart, 1997), and Q-factor model (Hou, Xue, and Zhang, 2015). The analysis is also robust when replacing the traditional value factor HML with the intangible-adjusted factor HML^{INT} (Eisfeldt, Kim, and Papanikolaou, 2020). The pattern is also not driven by specific industries as the results hold when we form the portfolio using within-industry-year break points. The return predictive power is also supported in Fama-MacBeth regressions in which we can flexibly control industry effects and a broad set of return predictors (Fama and MacBeth, 1973).

Why do firms with low (high) obsolescence in the current period bear high (low) abnormal return? In models of technological innovation and asset pricing, the *future risk* of displacement or becoming obsolete leads to a higher risk premium (Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, and Stoffman, 2020). This seems to suggest that high-obsolescence firms should have higher returns. The key insight to reconcile the evidence and the theory is: firms that experienced realized high obsolescence in the current period will face much lower obsolescence risk *in the* *future*—because their technologies were already destructed; while firms whose technologies have not yet became obsolete will face displacement risks in the future. As an empirical support to this insight, we show that the conditional volatility of the obsolescence measure is much higher in the next five years for firms with lower obsolescence in the current period. In contrast, we only find very mild evidence in support of a potential mispricing channel.

Related Literature. This paper complements to the broad set of models in macroeconomics that attempts to investigate the source of creative destruction and quantify its economic impact (Caballero and Jaffe, 1993; Caballero and Hammour, 1996; Acemoglu et al., 2018; Akcigit and Kerr, 2018; Garcia-Macia, Hsieh, and Klenow, 2019). One leading approach relies on calibration or estimation of structural models using reallocation data, labor reallocation data in particularly (Davis, Haltiwanger, and Schuh (1996) is the pioneer in this approach). In contrast, our approach builds a direct measure using detailed patent data and tests theoretical predictions. More related to this paper, BSV and KPSS construct patent-based measures by focusing on potential business stealing effects of competitors's innovation. We contribute to this line of work by proposing a new and patent-only measure of technology obsolescence without making assumption on product market competition and innovation spillovers. Moreover, this measure captures various sources of obsolescence and disruption, and provides independent information compared to these competitor's innovation measures.

More broadly, the ability to track innovation capital is a central question in the literature bringing intangible capital into macro models. The arrival of new innovation has been witnessing more effort.[6] However, the depreciation and destruction of innovation capital is equally important (Griliches, 1998; Corrado, Hulten, and Sichel, 2009; Crouzet and Eberly, 2020), and financial economics (Peters and Taylor, 2017; Eisfeldt, Kim, and Papanikolaou, 2020). The traditional approach estimate a uniform depreciation rate of R&D capital or intangible capital using accounting data (Mead, 2007; Eisfeldt and Papanikolaou, 2013; De Rassenfosse and Jaffe, 2017; Li and Hall, 2020; Ewens, Peters, and Wang, 2019) or using infrequent event-based approach such as patent renewal (Pakes and Schankerman, 1984). Our approach makes progress by relying heavier on the observation that annual citations are informative of technological revolution. Our measure is also in much finer unit at the firm-year level.

The paper is also related to the literature on the relation between technological innovation and

[6]For some other recent work that develop measures of new and novel innovation, see also Chen, Wu, and Yang (2019), Bellstam, Bhagat, and Cookson (2020), Bowen, Frésard, and Hoberg (2021), among others.

obsolete labor skills. Our paper focuses on firms rather than labor market outcome, but it shares the same rationale that new technology could outdate existing labor skills (Goldin and Katz, 1996, 1998, 2008; Autor, Katz, and Krueger, 1998; Autor, Levy, and Murnane, 2003; Autor and Dorn, 2013; Autor, Dorn, and Hanson, 2013; Deming and Noray, 2020; Biasi and Ma, 2021), or could completely substitute certain human capital with capital (Chari and Hopenhayn, 1991; Jovanovic and Nyarko, 1996; Violante, 2002; Hornstein, Krusell, and Violante, 2005, 2007). Our paper complements this literature by providing evidence from the perspective of firms, which are the demand side on the labor market.

The remainder of the paper is organized as the following. Section 1 presents details of constructing the measure of technology obsolescence. Section 2, 4, and 3 discuss the implications for firm behaviors, asset returns, and macro economic growth. Section 5 offers some concluding remarks.

1. Technology Obsolescence: Data and Measurement

This section describes the construction of our key technology obsolescence measure. We start by describing data collection. We then discuss the construction process of the key measure of *Technology Obsolescence*, its alternative variations, and the economic intuition. We also provide some validating examples and summarize the basic empirical properties of the measure.

1.1. Patent Information and Citation Data

Patent data are obtained from the United States Patent and Trademark Office (USPTO).[7] The database provides detailed patent-level records on nearly seven million patents granted by the USPTO between 1976 and 2020. It includes information on the patent assignee, and the patent's application and grant year. This database is linked to Compustat using the bridge file provided by NBER up to 2006 and from KPSS's data repository,[8] and for later year we complete the link using a fuzzy matching method based on company name, basic identity information, and innovation profiles, similar to Ma (2020) and Bernstein, McQuade, and Townsend (2021). Our main analysis focuses on US public firms between 1986 and 2016 over a thirty-year window. As discussed below, this window allows us to partially mitigate the truncation problems built in the patent data. That is, researchers do not observe full patent information of patents granted before 1976, and of patents

[7] We obtain the patent data from USPTO PatentsView platform, accessible at `https://www.patentsview.org/download/`.

[8] The extended data for KPSS can be accessed at `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`.

applied but not yet granted by the time of sample construction (Lerner and Seru, 2017).

Central to our analysis, for each patent p, we observe all the citations it makes to prior patents; and similarly, we also observe all the citations it receives from future patents up to 2020. For the former, those patents cited by p can be considered as the prior arts of p, as they capture the broad set of knowledge and technologies used in developing this new technology—we call these backward citations made by p. On average, each patent makes fifteen citations to prior patents. For the latter, we observe all cases when p is cited by a successfully granted patent, and timing of those citations. These are forward citations received by p. The forward citation process has a well known right-truncation problem (Hall, Jaffe, and Trajtenberg, 2001), because patents, particularly recent approved ones, could received many citations in the unobserved future. We will discuss this issue in the context of the analysis.

1.2. Constructing Technology Obsolescence

Next, we construct the technology obsolescence measure. We construct a firm(f)-year(t)-level variable, termed as *Technology Obsolescence*$^{\omega}_{f,t}$ (*Obsolescence* for short), to capture the ω-year (between $t-\omega$ and t) rate of obsolescence experienced by firm f as of $t-\omega$. The method builds on the literature of bibliometrics and scientometrics that measures the obsolescence and aging of a scientific discipline using the dynamics of citations referring to the specific field and its related documents. For each firm f in year t, and a given period of obsolescence ω, this variable is constructed in three steps.

Step #1: Technology Base. First, we define the technology base for each firm in each year. Firm f's predetermined technology base in year $t-\omega$ is defined as all the patents cited by firm f, but not belonging to f, up to year $t-\omega$. This fixed set of patents proxies for the underlying technological knowledge that firm f managed to accumulate up to $t-\omega$. We denote this set of patents as $TechnologyBase_{f,t-\omega}$. On average, a firm's technology base includes 2,001 patents (the median is 219 patents). From an academic researchers' experience, this is analogous to all the papers and books that are referenced in our research articles. Intuitively, this is a collection of technologies that is useful in firm f's innovation production and business operation. Removing f's own patents from the base minimizes the impact of f's own innovation decisions, while all results remain virtually the same when we include them.

Two properties about the technology base of each firm are worth noting. First, the technology base provides a reasonable proxy for the fundamental technologies that support each firm, and it shows strong persistence. We find that the expansion rate of a firm's technology base is slow—over the years, it ranges between 4–12 percent.[9] This suggests that subsequent innovation often is following up the prior foundation captured by the technology base, and this is also consistent with the findings in Akcigit and Kerr (2018).

[Insert Figure 1 Here.]

Second, even within an industry, firms' technology bases vary significantly, leading to the possibility to capture within-industry-year variations of the exposures to the technology evolution. Despite the within-firm stability of the technology base, there are sizable cross-firm variations of their technology base, even within the same industry. We calculate the pair-wise overlap ratio of firms' technology base. Each pair consists of two firms in the same SIC3 industry in the same year. We calculate their technology base overlap ratio as the number of patents in the base intersection over the number of patents in the union of the two bases. In Figure 1, we present the histogram of these ratios. Surprisingly, as shown in panel (a), more than 90% of the pairs have an overlap ratio of zero. In panel (b) in which we focus only on firms with at least 100 patents in their portfolios, the low-overlap pattern remains for firm pairs in the same SIC3 industry. This suggests that even among firms in the same narrowly defined industry, they are exposed to very different innovation paths and their potential disruptions.

Step #2: Technology Evolution and Citation Dynamics. Next, we measure the technological evolution around the technology base. We calculate the number of external citations received by this fixed $TechnologyBase_{f,t-\omega}$ in $t-\omega$ and in t, respectively. We denote them using the $Cit(\cdot)$ operator. The number of citations received by each patent in each year reflects the usefulness of the patent in helping generating new innovation in that year (Caballero and Jaffe, 1993). In other words, it captures whether the specific patent in the base is still at the technology frontier. We only track citations made by firms other than f itself. Excluding the citations made by the firm itself does not change the results significantly. This choice is motivated by the desire to capture technology evolution that is not directly driven by the firm's own contemporaneous shocks (like a financial shock, management decisions).

Despite that the technology bases are stable and persistent, technology evolution as reflected in citation dynamics shows sizable variations. In Appendix A.1 we provide an extensive discussion on the validity and aggregate patterns of citation dynamics of patents. We show time-series variations

[9] We want to cautiously note the left-truncation problem of citations data—but even with that problem, which could mechanically inflate the growth, the technology base shows mild growth at around 10% per year.

within each patent, i.e., patents go from unknown, to being widely cited, to cool down; and we also show cross-sectional variations across patents and technology fields of such citation dynamics. These give us the desired source of variations to the obsolescence measure defined below.

Step #3: Final Calculation. Last, $Obsolescence^{\omega}_{f,t}$ is defined as the rate of change between the two citations, Cit_t and $Cit_{t-\omega}$. Formally, the measure is defined in equation (1),

$$Obsolescence^{\omega}_{f,t} = -[\ln(Cit_t(TechnologyBase_{f,t-\omega})) - \ln(Cit_{t-\omega}(TechnologyBase_{f,t-\omega}))]. \quad (1)$$

A larger *Obsolescence* means a greater decline in the value and utility of a firm's knowledge within the ω-year period, as captured by the fact that fewer new patents build on that knowledge base. This is a within-firm growth measure, which naturally absorbs effects of the size of the firm and its knowledge space.

The measure is also quite flexible when accommodating different variations. As will be examined in the analysis sections, particularly in Section 2.5, *Obsolescence* can be constructed for different types of patents owned by a firm—core vs. peripheral (Akcigit, Celik, and Greenwood, 2016), embodied vs. disembodied (Bena and Simintzi, 2019; Kogan, Papanikolaou, and Stoffman, 2020). It can also be refined by only considering certain components in the base like more general-purpose technologies or standard essential patents. Those variations only involve minor changes in the construction process, but are helpful in exploring interpretations of our results.

1.2.1. Additional Discussions on the Construction. A natural alternative candidate to measure obsolescence is the changes of annual citations made to f's *own* patents. For example, if f's own patent portfolio receives 100 citations in 2000 and only 50 in 2005, that is a reasonable sign of f moving away from the technology frontier.[10] However, this measure is more exposed to alternative interpretations that will complicated our later analysis. For example, the performance of a firm's own patents could be heavily driven by a firm's own financial condition, technology decision, product market performance. Our construction—by using the base excluding f's own patents from the base, and tracking only citations not made by f—is closer to capturing the obsolescence driven by movements of technology frontier.

The construction of *Technology Obsolescence* replies on *only* patent data. It does not rely on any accounting data, does not assume product vs. innovation market competitors, does not rely on stock market data, and does not reply on resource reallocation data. There are certainly possibilities of

[10] In the Appendix, we show that this alternative measure yields even stronger results in all our analysis.

missing out useful information that may help refine the measure, but the benefits are also clear: the construction process does not need to introduce any assumptions on how competition or innovation spillover affect innovation activities, and we also do not introduce non-patent information which may be independent from science and technology.

1.3. Descriptive Statistics of ***Technology Obsolescence***

Table 1 shows summary statistics for technology obsolescence and other innovation measures in our sample. Our sample consists of US public firms between 1986 and 2016. Starting from 1986 allows ten years of stable patent data availability with citation information to calculate the obsolescence measure. Stopping in 2016 allows us to partially address the right truncation problem of patent citation—the number of patents drops significantly after 2017 due to the gap between filing year and granted year, thus citations made by those patents would be noisily measured.

We first report the *Obsolescence* measure for different ω horizons, $\omega = 1, 3, 5, 10$. Using $\omega = 1$ as the illustrative case—on average, a firm's technology base constructed in $t-1$ receives 7.84 percent fewer citations in year t compared to the year before, noting that a positive *Obsolescence* means a lower citation count in the later period. The measure also shows wide variations. Firms riding an upward trend enjoy a low obsolescence at -8.04% at the 10th percentile, which means that their technology bases receive 8.04 percent more citations of the period; while on the opposite end, with the highest 10 percent *Obsolescence* firms, their obsolescence measure is at 24.20%, meaning the technology base receive 24 percent fewer follow up citations.

[Insert Table 1 Here.]

We also summarize measures that capture the arrival of new innovation, particularly the stock market-based patent value (SM), and the citation-weighted patent counts (CW). They represent the number of patents weighted by the value measured using stock market reactions to their approvals, and the scientific value captured using the number of total forward-looking citations. Both of the values are scaled by book assets of the firm to remove the size effect. Those two measures are convincingly validated in KPSS, and we refer interested readers to KPSS for details.

The arrival of new innovations are infrequent and is highly skewed across firms. This is consistent with the prior literature noting that most firms do not patent frequently, if at all; and that the citations received by patents are highly skewed. Our analysis focuses on the sample of firms that are more innovative, defined as firms that were granted at least 10 patents at some point in their life, even though all our results hold in broader samples. This explains why our summary statistics of new innovation are larger in magnitude compared to the original KPSS paper.

1.4. Decomposition of *Technology Obsolescence*

1.4.1. Industry, Firm, Time. *Obsolescence* can vary across industries, across firms within an industry, and within a firm (over time). In Table 2, we first decompose total variation in *Obsolescence* into these three components. The first two columns report the proportion of obsolescence variation attributable to each component. We define industries by SIC3. We note that, technology obsolescence varies more in the time series than cross-sectionally. Roughly 60 percent of *Obsolescence* variation is within-firm over the time-series. Of that 40 percent cross-sectional variation, the majority is across firms within a given industry (30 percent), rather than between industries (10 percent).

[Insert Table 2 Here.]

In columns 3 and 4, we extend the decomposition exercise and break the total variation into across industries, across industry-year but within the same industry, and within industry-year but across firms. The largest proportion of variation is from within the same industry-year, scoring 60 percent. Across industry-year, but within the same industry, the variation is 30 percent of the total. These two patterns tell us: industry-year trend is important for capturing technology evolution; during the same trend, there are winners and losers, creating large heterogeneity across firms.

1.4.2. Sources of Technology Obsolescence. We also explore the correlation between the *Obsolescence* measure with several potential sources of new innovation that could outdate a firm's existing technological capital. In specific, we know that a firm's existing technology could be rendered obsolete by several sources (Garcia-Macia, Hsieh, and Klenow, 2019; Kogan et al., 2020). A firm's technology obsolescence could originate from cannibalization by the firm's own new innovation (Christiansen, 1997; Igami, 2017), by a firm's industry rivals' new technological breakthroughs (BSV, KPSS), or from innovation from outside the boundary of the specific industry (imagine AirBnB disrupt hotels; iPad and Kindle disrupt traditional printing copies).

[Insert Table 3 Here.]

In Table 3, we perform a very simple analysis to project *Technology Obsolescence* on three other new innovation predictors—the firm's own innovation over the same ω years for which the obsolescence measure is constructed, the industry leave-me-out new innovation, and the overall innovation index of the economy. The simple analysis suggests that technology obsolescence is associated with all three potential sources of technology disruption, and they seem to share similar magnitude in terms of affecting technology obsolescence. For instance, in columns (1) and (2) we examine the impact of a firm's own innovation, industry's leave-me-out innovation, as well as new innovation, and innovation from the upstream (e.g., bio-engineering is upstream for pharmaceutical) as defined in Acemoglu, Akcigit, and Kerr (2016).

1.5. A Case Study: HDD Industry, 1985 to 1995

Before entering the analysis stage, we provide a case study to illustrate how our technology obsolescence measure can capture the evolution of technology. To do so, we need a well-defined setting in which technological evolution can be clearly traced, and patents are a clear reflection of such evolution.

The setting we use is the Hard Disk Drive (HDD) industry.[11] This industry has been an innovation economists' favorite for a few decades (Christiansen, 1997; Igami, 2017), for a few reasons. First, it is an important sector in the computer industry that has been innovation-intensive since the late 1970s. Second, despite generations of innovation, HDD's main function as a data storage device remain the same and well-defined. Third, different generations of HDD can be coarsely classified using their form-factor (e.g., 5.25-inch, 3.5-inch, 2.5-inch).

Our case study focuses on the time window between 1985 and 1995, during which the industry transitioned from 5.25-inch-dominant to 3.5-inch-dominant. The basic logic to validate our measure is: when 3.5-inch technology started to emerge in the industry, those technologies that support the 5.25-inch HDD would become obsolete (citations decrease, and the obsolescence measure increases). Instead of showing this using firm-level obsolescence, we show this using patents for easy comparison (one could imagine that we are comparing firms with a single patent).

[Insert Figure 2 Here.]

We show this in two pairs of examples, corresponding to two different types of core technologies associated with building HDDs.[12] The first pair of patents that we compare are general-design

[11] We thank Michi Igami for helpful discussions. The examples are also intrigued by Dr. Tu Chen's book, entitled *The Evolution of Thin Film Magnetic Media and Its Contribution to the Recent Growth in Information Technology: My Personal Experiences In Founding Komag, Inc.*

[12] For readers interested in learning more about HDD patents, we hereby describe our procedure used in building the patent set for the case study. To identify HDD-related patents, we follow Igami and Subrahmanyam (2019) and

patents of HDD. For 5.25-inch, there is patent 4935830 ("Electro-Magnetic Shield Structure for Shielding A Servo Megnetic Head of a Magnetic Disk Storage Device"); for 3.5-inch, there is patent 5027242 ("Magnetic Disk Apparatus Having At Least Six Magnetic Disks"). In Figure 2 panel (a) and (b), we find that the obsolescence scores of those two patents differ significantly, and the trends diverge at the end of 1980s. Similarly, we find another pair of patents that represent the design of the head arm of HDD. For 5.25-inch, there is patent 4764831 ("Apparatus and Method For Retaining A Head Arm of A Disk Drive Assembly"); and for 3.5-inch, there is patent 4933791 ("Head Arm Flexure For Disk Drives"). Again, we observe that the 5.25-inch head arm patent's obsolescence became significantly worse than the 3.5-inch counterpart during the transition.

2. Technology Obsolescence and Firm Growth

This section starts to test predictions on the role of technology obsolescence generated from models of endogenous growth (Grossman and Helpman, 1991; Aghion and Howitt, 1992; Klette and Kortum, 2004; Lentz and Mortensen, 2008; Acemoglu et al., 2018; Garcia-Macia, Hsieh, and Klenow, 2019). In those models, firms' existing innovation portfolios are destructed at a certain rate, leading to technology obsolescence. Realized technology obsolescence is followed by lower output and profits of the firm, and also reallocation of capital and labor away from the firm. We jointly analyze technology obsolescence with the arrival of new innovation, and with the alternative measures of technology disruptions based on competitors' new invention (i.e., "competitors' win is my loss"). We discuss the insights generated from those comparisons and explore the potential reasons behind them.

2.1. Method

Our main analysis follows KPSS closely and takes the form of equation (2). As dependent variables Y, for firm growth and productivity, we iteratively use profits (Compustat item `sales` minus Compustat item `cogs`, deflated by the CPI), nominal value of output (Compustat item `sales` plus change in inventories as Compustat item `invt`, deflated by the CPI), capital stock (Compustat item `ppegt`, deflated by the NIPA price of equipment), number of employees (Compustat item `emp`), and revenue-based productivity (TFPR, constructed based on the methodology of Olley and Pakes

focus our main example search among patents in that are coded as NBER patent category "360 - Dynamic Magnetic Information Storage or Retrieval," which are shown to be the most relevant for HDD manufacturing quality. We further narrow our search to patents that explicitly mention "5.25-inch" and "3.5-inch" in their patent abstracts, and the patent texts are from the USPTO website.

(1996) using the estimation procedure in İmrohoroğlu and Tüzel (2014)).

$$\log Y_{f,t+\tau} - \log Y_{f,t} = \beta_\tau \cdot Obsolescence_{f,t} + \theta_\tau \cdot X_{f,t} + \delta_{I\times t} + \varepsilon_{f,t+\tau}. \tag{2}$$

We explore growth horizons τ of one to five years. The version of *Obsolescence* presented in the main text takes $\omega = 5$, and ω parameter is omitted in this and later equations.[13] In other words, the timing in the analysis is: taking $t = 2000$, we use the technology obsolescence measured between 1995 and 2000 to explain firm growth between 2000–2001, 2000–2002, ..., and 2000–2005. The obsolescence measure is normalized to unit standard deviation so it can be conveniently interpreted quantitatively and be compared with other innovation measure with other units. This is a growth-on-growth framework after taking out fixed firm-level characteristics, as the *Obsolescence* measure is a rate of citation changes to the firm's technology base.

Following KPSS, we include in the set of control variables, $X_{f,t}$, the level $\log Y_{f,t}$, the log value of the capital stock, the log number of employees, and the log number of patents granted up to year t, to alleviate the concern that firm size may introduce some mechanical correlation between the growth variables and the obsolescence measure. For example, larger incumbent firms tend to growth slower and may also be more exposed to obsolescence in their patent portfolio. We also control for firm idiosyncratic volatility. All measures are winsorized at the 1% and 99% level. Details of variable constructions are discussed in the Appendix. Table 4 provides summary statistics at the firm-year level.

[Insert Table 4 Here.]

In all our analysis, we include SIC3-by-year fixed effects to account for unobserved factors at the industry-year level. So all the results are estimated exploring cross-sectional variations across firms in the same SIC3 industry at the same point in time. Standard errors are clustered by both firm and year.

2.2. Baseline Results: Firm Growth and Resource Allocation

We first estimate equation (2) with the firm growth and productivity measures, and report results in Table 5. We see negative estimates of βs across the growth rate of profits, output, capital, and employees. A one standard deviation higher in obsolescence is associated with lower profits and output of 2.1 and 2.5 percentage point, respectively, over a five-year horizon. We also observe a

[13] The main analysis with other ω parameter values are presented in Appendix Table A.1 and Table A.2.

gradual reallocation of resources away from the obsolete firm. Capital stock decreases by 4.5 percent during the same five year period, and total employment decreases by 1.5 percent. We find that a one standard deviation increase in technology obsolescence is associated with a 1.1 percentage point lower in productivity measured using TFPR over five years.

[Insert Table 5 Here.]

Next, we compare the technology obsolescence measure with the new innovation measures. The analysis follows the same structure as in equation (2), but add to the analysis SM and CW. To facilitate interpretations, these measures are also scaled to unit standard deviation. The analysis results are shown in Table 6.

[Insert Table 6 Here.]

We can make three observations. First, technology obsolescence captures additional and largely independent variations in a firm's innovation portfolio compared to the earlier measures. Comparing the point estimates of βs in Table 6 with those in Table 5, we find virtually no change in both economic magnitudes and statistical significance. This suggest the *Obsolescence* measure achieves the goal of capturing the fading of a firm's existing technology, which can be quite empirically independent from the arrival process of new valuable innovation.

Second, technology obsolescence outperforms the well-established pure patent-based measure, CW. The fragility of the citation-weight patent count measure is documented in KPSS and papers cited therein. One potential reason behind the improvement in the explanatory power of our measure is the better use of all historical and time-varying information of patent citations.

At last, the arrival of new innovation has stronger, often 1.5 to 3 times of those of obsolescence, and more immediate influence on firm growth and expansion. In other words, the impact of technology obsolescence is milder and slower. This new finding is useful to map to the observed trend in the creative destruction process—innovative firms quickly climbs up with the help of new innovation, while obsolete incumbents remain in the industry for a long time.[14]

Why is technology obsolescence associated with lower performance? If the technology market is complete—in the sense that ideas and human capital are of abundant supply and can be traded and adjusted freely, the effect of a technology obsolescence position should have at most mild effect

[14]This is also consistent with our findings when exploring extreme outcomes such as bankruptcy, presented in Appendix Table A.3. We found mild and statistically noisy effect of obsolescence leading to bankruptcy in the next five years.

as firms can always regain the position through learning, acquiring human capital, and innovating. However, there are at least two potential frictions that make technology market incomplete, leading to substantial destruction associated with obsolescence. First, knowledge begets knowledge. Isaac Newton said, "If I have seen further it is by standing on the shoulders of Giants." Indeed, the knowledge stock of an innovative individual or institution determines the quantity and quality of its innovation and knowledge production (Jones, 2009). BSV show that firms working in a fading area benefit less from knowledge spillover, which in turn could dampen growth in innovation and productivity.

Second, knowledge absorption and update is not friction-less. In fact, the process can be difficult and slow. For any individual or institution, knowledge can be identified, absorbed, and managed at a limited rate (Cohen and Levinthal, 1990). Even for firms, which have the option to replace human capital (innovators), the adjustment costs and uncertainty associated with the matching process limits their ability to do so. The adjustment of technology is often associated with costly capital adjustment as well (Caballero and Jaffe, 1993; Bertola and Caballero, 1994)—upgrading technology involves liquidating vintage capital, installing new capital, and training new human capital.

2.3. Heterogeneity: Innovation Types and Market Competition

Economic theories not only predict the relationship between innovation and firm growth, but also predict that the effects of technology obsolescence differ with the types of technology that become obsolete and with product market conditions. In Table 7 we present several key heterogeneity analysis. Appendix Table A.4 presents this analysis with alternative control variables.

[Insert Table 7 Here.]

The first cut of the data is based on whether the technology that becomes obsolete is central to a firm's innovation portfolio—core vs. peripheral patents. Akcigit, Celik, and Greenwood (2016) and Ma, Tong, and Wang (2021) show that values of core patents (say a engine-related patent for an automaker) are higher for a firm than those of peripheral patents (say an entertainment system patent for the automaker). In columns 1 and 2 of Table 7, we construct two more granular versions of *Obsolescence*, one using the technology base of a firm's core patents, i.e., patents cited by a firm's core patents; and the other using the technology base of the non-core patents. Core and non-core patents are categorized based on whether the patent category belongs to the main categories of the firm—defined as those top patent categories that includes 50% of the patents.

We then introduce those two versions of *Obsolescence* measure into our main model in equation (2). Due to limited space, we only use $\tau = 3$, the three-year time horizon, as the dependent variable. We find that the obsolescence of a firm's core patents drives most of the findings. In profit and output analysis, the effect of technology obsolescence of peripheral patents is negligible. For capital, labor, and TFP growth, peripheral patents remain relevant, but the economic magnitudes are lower than those for core patent, and the statistical significances are often fragile.

In columns 3 and 4, we separate technology bases depending on whether they are serving for product or process innovation. The categorization of product or process innovation is based on the textual component in the claims of the patents. Following Bena and Simintzi (2019), we denote a patent as process patent if the first claim begins with "A method for" or "A process for" followed by a verb (typically in gerund form), and the residual are denoted as product patents. We find the effect to be stronger for obsolescence in product innovation. This is consistent with the theoretical underpinning about embodied and disembodied innovation (Berndt, 1990). These papers argue that process (disembodied) innovation takes the form of improvements in labor productivity and are complementary to existing investments; in contrast, product (embodied) innovation may are embodied in new vintages of capital and may lead to more creative destruction (Kogan, Papanikolaou, and Stoffman, 2020).

We investigate the role of product market competition in columns 5 and 6. In this case, we cut the sample by SIC3 industry's Herfindahl-Hirschman Index (HHI). The relation between product market competition and the production of innovation is an unsettled debate (Cohen, 2010; Aghion et al., 2005). We find that the obsolete firms decline much faster in competitive industries. For instance, in a high-HHI industry, a one standard deviation increase of obsolescence is associated with a 3.6 percent decrease of capital stock and a 1.8 percent decrease of total employment within the three year horizon. While these decline are virtually zero for industries where competition is less fierce. The implication of this result is interesting—creative destruction is facilitated by product market competition (Aghion et al., 2009; Cunningham, Ederer, and Ma, 2021).

2.4. Comparing With Other Measures of Technology Destruction

Next, we compare our measure with other measures of technology disruption experienced by each firm. The most influential construction of such measures is the leave-me-out industry innovation. These measures are calculated based on collective innovation output of each firm f's product market competitors. For two recent examples, KPSS construct a SM competitor measure by aggregating all SM patent value of firms in the same SIC3 category. BSV also aggregates innovation activities measured using R&D input by competitors.

These measures have strong economic intuition—indeed, in a wide range of innovation models, "competitors' win is my loss." These measure also have impressive successes in showing how competitors' innovation breakthroughs may disrupt the focal firm's own growth. However, as noted in both BSV and in KPSS, this approach replies on several strong assumptions. (i) This approach does not take into account innovation disruptions that could be originating from outside a firm's own industry, which is particularly true for novel innovation (AirBnB disrupts hotels, Email disrupt postal services). It also does not account for non-corporate inventors, or from within-firm cannibalization. (ii) It relies on the assumption of one's industry peer group and of the homogeneous relevance of industry competitors. This assumption appears to be very strong given what we document above in Figure 1 that even firms in SIC3 share limited innovation overlaps. (iii) The "leave-me-out" type of construction of a firm-level variable is often highly correlated with time variant industry trends, which are quite crucial to control for in innovation studies (Kelly et al., 2021; Lerner and Seru, 2017). (iv) Due to the dependence on industry classification, the measure often can only be constructed for public firms, and often works the best for firms with un-diversified industry coverage.

[Insert Table 8 Here.]

In Table 8, we compare our *Obsolescence* measure with the leave-me-out industry innovation measures using the same empirical model in equation (2). Technology obsolescence preserves its economic importance and statistical robustness. Without any intention to over-interpret this result, we read this finding as suggesting that our obsolescence measure provide additional information compared to the earlier "leave-me-out" style measures.[15] Moreover, in most of the analysis, technology obsolescence seems to more robustly explain firm profitability and growth patterns, compared to SM of competitors. The coefficients associated with Competitors' SM are consistently of reasonable signs and are of marginal statistical significance. Note that this is in our preferred setting in which we control for granular industry-by-year fixed effects.

Overall, our measure contributes to the task of capturing technology disruption at the firm-level. It could be due to the fact that the construction of *Obsolescence* better takes out technology and market trend common for a specific industry by making use of the granular innovation portfolio of each firm. It accounts for the possibility that disruptive innovation may happen outside of a

[15] Competitors' CW leads to highly noisy results, consistent with those in KPSS, and are omitted from the table.

pre-defined industry, especially for modern and innovative firms whose industries are harder to categorize. It also considers that even within the same industry, competitors' innovation could have positive or negative impact as documented in BSV. At last, it takes into consideration that many disruptive innovation are in fact produced internally and cannibalize internal innovative stock (Igami, 2017; Garcia-Macia, Hsieh, and Klenow, 2019).

2.5. Strengthening *Obsolescence*-Driven Interpretations

As in KPSS, our firm-level tests do not intend to establish a causal statement between technology obsolescence and firm-level performance. Specifically, one may be worried that the main measure reflects information beyond technology but could be predictive of future firm performance—such as financial condition, management skills, among others. In other words, the potential contamination arises from the following concern: If a firm experienced a negative non-innovation shock, such as poor management or financial constraints, the firm would be less capable of promoting its technologies, which could reversely "cause" technology obsolescence to fall. These concerns are already guarded by two parts of the analysis so far. First, as described in Section 1.2.1, we mitigate the influence of a firm's own decisions through excluding the firm's own patents from the technology base, and through removing all citation made by the focal firm from calculating the obsolescence measure. In this way, any direct influence of a firm's own business conditions are mitigated.

Second, the heterogeneity analysis documented in the previous section elevate the bar for any alternative interpretation that may function without technology obsolescence. For instance, an alternative interpretation would need to explain why, without through the technology channel, that core (peripheral) patents have stronger (weaker) influence on future firm performance. Similarly, the mechanism needs to explain the heterogeneity across product (embedded) vs. process (dis-embedded) innovation.

Despite those prior effort, we would like to further strength the technology obsolescence-driven interpretation. In the Appendix, we provide several additional variations of the *Obsolescence* variable. Most of those variations aim to isolate the obsolescence originating from part of the base that are less contaminated by a firm's own recent past operations and performance. The central motivating principle in those additional analysis is: we want to construct the technology base using only patents that are more scientific and less firm-specific. In other words, we want to capture the obsolescence driven by scientific discoveries and advancements. In Appendix Table A.5 we only build the technology base using patents that are top-tercile general-purpose, defined as in Hall, Jaffe, and Trajtenberg (2001) using the dispersion of citations across patent classes. Table A.6 uses others components in the base that are more irrelevant to the focal firm's own business condition—international patents, patents owned by non-corporations (government, universities, etc.), and patents that are categorized as standard essential patents (SEP) as proposed in Lerner and Tirole (2015) and classified by Baron and Pohlmann (2018).

3. Lessons from Aggregation

This section analyzes the aggregate effect of technology obsolescence. New innovation drives growth, but the resulting technology obsolescence leads to value loss of the physical, human, and organizational capital embodying the obsolete technology (Caballero and Hammour, 1996). When certain technology becomes obsolete, outdated capital will be destroyed; and it could also entail substantial job losses. This could be due to that the outdated capital and labor are of high degree of specificity, making the reallocation and redeployment challenging. Or that the new technology requires new rounds of learning-by-doing (Stokey, 1988), leading to short-run slow growth.

The goal of this section is to quantify these costs. Understanding these cost can help us better account for the aggregate value of new innovation and design innovation policy (Garcia-Macia, Hsieh, and Klenow, 2019). We perform two analysis. First, we use firm-level estimates of Section 2 to examine the net impact of technology obsolescence on aggregate output and productivity. Second, we construct a simple aggregate index of technology obsolescence for the whole economy, and relate the index to aggregate output and productivity.

3.1. Aggregation Impact of Technology Obsolescence

We start by trying to quantify the aggregate impact of technology obsolescence using our empirical estimates in Section 2. Those estimates are at the firm-level within our sample of publicly traded firms, and are estimated in terms of growth rates. To obtain the aggregate impact of technology obsolescence, we first compute the portion of the dollar change in the size Y of firm f between time t and $t+\tau$ that is associated with the obsolescence of its own technology,

$$\hat{Y}_{f,t+\tau} - \hat{Y}'_{f,t+\tau} = \Big[\exp\big(\hat{\beta}_\tau \cdot \mathit{Obsolescence}_{f,t} + \hat{\theta}_\tau \cdot X_{f,t}\big) - \exp\big(\hat{\theta}_\tau \cdot X_{f,t}\big)\Big] \times Y_{f,t}, \tag{3}$$

where we make use of the estimated regression coefficients from model (2), $\hat{\beta}_\tau$ and $\hat{\theta}_\tau$ on the horizon, τ. Here, we use the notation Y' to refer to the counterfactual level of Y in the no-obsolescence case—or in other words, when the *Obsolescence* measure is uniformly set to 0.

Second, we aggregate these estimates across all firms in the sample to obtain the average component of technology obsolescence over the whole sample period,

$$G_\tau = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{\tau}\frac{\sum_f(\hat{Y}_{f,t+\tau} - \hat{Y'}_{f,t+\tau})}{\sum_f Y_{f,t}}\right]. \tag{4}$$

In equation (4), the numerator and denominator sum across all firms in our sample that survive to time $t+\tau$. The term inside the brackets can be interpreted as the annualized aggregate destruction rate between periods t and $t+\tau$ that is related to technology obsolescence, subject to two caveats: (i) we omit some general equilibrium effects due to the presence of time dummies in equation (2), and (ii) our estimate aggregates outcomes within our sample of public firms that patent frequently.

To assess the magnitudes of equation (4) we compare it to its realized counterpart,

$$g_\tau = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{\tau}\frac{\sum_f(Y_{f,t+\tau} - Y_{f,t})}{\sum_f Y_{f,t}}\right], \tag{5}$$

which can be considered as the realized annualized real growth rate of firms in our sample.

In Table 9 we report our estimates for G and g, and the ratio of the two. Our estimates imply that the destruction of technology obsolescence is quite substantial. For instance, in a setting with $\tau = 5$, our estimate of G_5 implies that technology obsolescence can account for an average net destruction rate of 0.31 percentage point in firm profits, 0.39 percentage point in firm output, 0.76 percentage point in capital, and 0.22 percentage point in the number of employees. When we benchmark those numbers using mean aggregate growth rate for the corresponding variables g_5, *Obsolescence*-related value loss is around 9 percent to 14 percent of net economic growth every year in profits, output, and capital.

[Insert Table 9 Here.]

We want to make a note on the results concerning labor. The size of the labor destruction scaled by the average growth, G/g, is large and scores the magnitude of around 40 percent when $\tau = 1$ and 25 percent when $\tau = 5$. This doubles or even triple the *Obsolescence*-related loss on other outcomes. This could be sign that technology obsolescence could be particularly disruptive to human capital owned by workers (Rosen, 1975; Gârleanu, Kogan, and Panageas, 2012; Aghion et al., 2016; Kogan et al., 2020).

3.2. Economy-wide Obsolescence Index

Next we construct an economy-wide index of technology obsolescence, and examine its correlation with measures of aggregate productivity and economic growth. We construct the rate of technological obsolescence as the average of *Obsolescence* across all firms in our sample, weighted by firm-year market value $s_{f,t}$:[16]

$$\overline{Obsolescence}_t = \frac{\sum_f Obsolescence_{f,t} \cdot s_{f,t}}{\sum_f s_{f,t}}. \tag{6}$$

A benefit with the index (6) is that its fluctuations are less related to fluctuations in the aggregate level of economic outcomes that we aim to explain. Instead, this measure captures the scientific decline of the technology stock of incumbent firms. We plot the obsolescence index, both value-weighted and equal-weighted, in Figure 5. In Figure A.6 we show the evolution by industries.

[Insert Figure 5 Here.]

How does the obsolescence index explain fluctuations in aggregate growth? We examine the extent to which our index accounts for short- and medium-run fluctuations in aggregate output growth and productivity in the following simple framework:

$$y_{t+\tau} - y_t = \lambda_0 + \lambda_\tau \cdot \overline{Obsolescence}_t + \sum_{l=0}^{L} c_l \cdot y_{t-l} + u_{t+\tau}. \tag{7}$$

Here y is our variables of interest that captures aggregate output including the per capita GDP deflated by the consumer price index, and productivity as the utilization-adjusted TFP from Basu, Fernald, and Kimball (2006), and both are logged. We also include the lagged measures of new innovation index from KPSS. We examine horizons of one to five years. We select the number of lags L using the Bayesian information criterion, which advocates a lag length of one to three years depending on the specification. We compute standard errors using Newey-West with a maximum lag length equal to $\tau + 4$.

[Insert Figure 6 Here.]

In Figure 6, we plot the response of aggregate output and TFP to a unit standard deviation shock in our obsolescence index. Over a period of five years, a one standard deviation increase in our index is followed by approximately a 4 percent decrease in output growth and a 0.8 percent decrease in

[16] All our results shown below remain robust if the index is calculated using equal-weighting.

aggregate productivity. The result holds for both equal-weighted and value-weighted indices. In sum, we find that the destruction associated with technology obsolescence are substantial. In other words, the growth associated with technology improvement has left behind and destructed a significant amount of assets. These results are consistent with the estimates obtained from aggregating the coefficients from the firm-level analysis in Section 2.

This finding is in contrast to Shea (1998), who finds only a weak relation between simple patent measures and measured TFP. This is consistent with the message in KPSS in which innovation arrivals captured using stock-market responses are associated with growth despite the potential disruption. Our aggregation results also remain robust if we control for new patent arrival measures and competitors' new innovation measure as in KPSS. At the minimum, our finding suggests that the obsolescence index contains useful incremental information about aggregate growth and productivity relative to what is included in simple patent counts.

4. Asset Prices and Cost of Financing Innovation

In this section, we test the asset pricing implications of technology obsolescence. Doing so can help us better understand the risks associated with technology evolution and the cost of funding breakthrough innovation. We first show our analysis and results, then discuss their connections to existing literature on technology evolution and stock returns.

4.1. Method

We draw monthly stock returns, shares outstanding, and volume capitalization from the Center for Research in Security Prices (CRSP). These are merged with Compustat variables and patent data described in the previous section. Our sample includes all NYSE, AMEX, and NASDAQ common stocks (CRSP share code 10-12) with an *Obsolescence* measure for the year. In addition, we omit financial firms (SIC codes 6000 to 6799) and utilities (SIC codes 4900 to 4949).

We first conduct portfolio sorts to illustrate the abnormal returns, and then use Fama-MacBeth regressions to show the robustness of the effect against other return predictors.

4.2. Sorted Portfolio

We start by examining average returns on portfolios formed using *Obsolescence*. At the end of June of year t from 1986 to 2016, we sort firms into three portfolios—Low, Middle, High—based on *Obsolescence* from the prior calendar year $t-1$. The Low-*Obsolescence* portfolio contains all stocks below the 30th percentile in *Obsolescence*, and the High-*Obsolescence* portfolio contains all stocks above the 70th percentile. Based on our formation of the technology obsolescence, the measure is publicly observable at the end of year $t-1$ and does not incorporate any forward-looking information. We hold these portfolios over the next twelve months, from July of year t to June of year $t+1$. We compute value-weight monthly returns and equal-weight monthly returns for those portfolios. No additional filters are used in selecting the sample although the results are robust to additional filters like the commonly used price filter (e.g., lagged share prices above five dollars).

[Insert Table 10 Here.]

In Table 10 panel (a) we study average value-weighted monthly returns. Column 1 shows the portfolio returns in excess of one-month Treasury-bill rate. The excess returns monotonically decrease with the obsolescence measure. The magnitude is economically and statistically significant. To examine the obsolescence-return relation, we form a portfolio that take a long position in the Low-*Obsolescence* portfolio and a short position in the High-*Obsolescence* portfolio. The monthly buy-and-short portfolio return is 30 basis points, which translate to 3.7 percent annually. Appendix Table A.8 shows that Low and High portfolios are in fact quite similar across many important characteristics. For example, in percentiles, they are similar or virtually the same on size (46th vs 48th), book-to-market (46th vs 54th), R&D ratio (49th vs 50th), short-term momentum (91th vs 49th), idiosyncratic volatility (54th vs 51th), patent counts scaled by assets (49th vs 51th).

We next extend our analysis by performing time-series regressions of the portfolios' excess returns on a vast set of risk factors. In specific, we consider the Fama-French three factors (Fama and French, 1992), namely the market factor (MKT), the size factor (SMB), and the value factor (HML); we also consider the momentum factor (UMD) (Carhart, 1997) which helps form the four-factor model. We also consider a model with the four factors and the Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA) factors (Fama and French, 2015). We obtain the q-factors developed in Hou, Xue, and Zhang (2015). At last, we also consider the intangible capital-adjusted HML factor developed in Eisfeldt, Kim, and Papanikolaou (2020). We replace the traditional Fama-French HML factor with HML^{INT} in the factor models and report those results.

The alphas obtained from those models are reported in the remaining columns in Table 10. There is a consistent pattern of monotonic relation between *Obsolescence* and abnormal returns. In fact, in those models, the High-*Obsolescence* portfolio carries a negative abnormal return. The Low-*Obsolescence* portfolio has a positive alpha. The Low-Minus-High spread portfolio scores between 36 and 59 basis points monthly, which translate to between 4.40 percent and 7.31 percent annually. The findings hold true for equal-weight portfolios as reported in panel (b). The results are also robust when we sort the portfolios into five quintiles rather than three, and the results are reported in Appendix Table A.9. Those effects remain robust when we calculate abnormal returns using portfolio returns adjusted by industry, Size/BM, and Size/BM/Momentum, the results are reported in Appendix Table A.10. The effect is also robust when we perform the portfolio sorting using by-industry breakpoints each year or using industry-year-demeaned *Obsolescence* measure, shown in Table A.11.

In panel (c) we report the four-factor loadings of these portfolios. The Low-*Obsolescence* portfolio loads negatively on the value factor, meaning that these stocks are typically growth stocks. The portfolio does not seem to load heavily on size or momentum. In contrast, the High-*Obsolescence* portfolio loads positively on the value factor. The Low-Minus-High portfolio loads negatively on value. In a similar spirit, we find that the spread portfolio loads positively on the intangible asset-adjusted value factor (Eisfeldt, Kim, and Papanikolaou, 2020), the portfolio loads positively on the investment factor (Hou, Xue, and Zhang, 2015). These results, together with portfolio loadings on additional risk factors, are reported in the Appendix Table A.12.

[Insert Figure 3 Here.]

We also visualize the dynamics of the abnormal returns in Figure 3 and find virtually no reversal. We plot the cumulative abnormal returns (CARs) of the spread portfolio following the portfolio formation, denoted as time 0, for 72 months. The CARs are based on the monthly Size/BM/Momentum-adjusted ($5 \times 5 \times 5$) abnormal returns. Returns of spread portfolios are large and significant in the first 48 months, and then the return flattens. Even continuing the graph on into later years, there is still no reversal in returns, suggesting a simple overreaction mechanism cannot reconcile with our findings.

4.3. Cross-sectional Returns

Next, we examine the ability of technology obsolescence to predict the cross section of stock returns using monthly Fama-MacBeth regressions. Compared to the simple portfolio sorting approach, this approach allows us to control a more extensive set of firm and industry level characteristics that can affect stock returns. Following Fama and French (1992), we allow for a minimum of six-month lag between the accounting variables and the stock returns to ensure full observability. That is, for each month from July of year t to June of year $t+1$, we regress monthly returns of individual stocks on *Obsolescence* as of $t-1$. We perform the analysis with different permutations of control variables and fixed effects.

[Insert Table 11 Here.]

In Table 11 we report the results. We standardize all independent variables to unit standard deviation to facilitate interpretations. The key result of interest is the time-series average slopes from the monthly cross-sectional regressions. We report the Newey-West heteroscedasticity-robust and autocorrelation-adjusted standard errors. All the variables used in the analysis are only briefly discussed here, and are defined with details in the Appendix.

We start from a univariate regression in column 1. The slope on *Obsolescence* is -0.187% ($t = 2.43$). In column 2, we add to the model widely used controls including *Size* (the log market value of equity); $\log(BM)$, the log book value of equity over market value of equity; $Ret(-1,0)$, the previous month's return which captures the possibility of short-term return reversal; $Ret(-12,-2)$, the cumulative stock return from month $t-12$ to month $t-2$, capturing momentum. We also introduce the measure of idiosyncratic volatility, measured at the end of June of year t as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months with a minimum of 31 trading days. We add $t-1$'s (or last quarter's) standardized unexpected earnings surprise (SUE). In column 3, we add to the model a broad set of innovation-related variables following those in Hirshleifer, Hsu, and Li (2018). These include Patents/Assets, R&D/Market Equity, Innovation Originality, Citation-based and Patent-based innovation efficiency. In column 4, we add to column 4 industry fixed effects to control for any industry-level characteristics that may be driving our results. In columns 5–8, we report the unweighted OLS version of the results.

4.4. Discussion: Obsolescence Risk and Stock Returns

So far, the results show that obsolete firms have lower stock returns, and this is true after adjusting commonly used risk factors and firm-level characteristics. Why? Technological changes are an important source of economic risks that are priced in asset prices (Kogan and Papanikolaou, 2019). A commonly shared idea in those models is that the *future* risk of displacement, or equivalently, of becoming obsolete, leads to a higher risk premium. In contrast, firms with lower displacement risks in the future should have lower returns.

At the first glance, our high obsolescence-low return result seems to contradict with this rationale. But in fact, it does not. The key insight is: firms that experienced *realized* high obsolescence in the current period will face much lower obsolescence risk in the future—because their technologies were already destructed. Firms whose technology did not yet become obsolete, on the other hand, will face displacement risks in the future. As a result, the portfolio with high (low) realized obsolescence today will bear lower (high) risk premium in the future.

[Insert Figure 4 Here.]

Figure 4 shows this intuition. In panel (a), we plot future obsolescence dynamics after portfolio sorting using realized *Obsolescence* at t, from $t+1$ to $t+10$. We can see that the low-*Obsolescence* portfolio experiences an increase in future obsolescence in the five years subsequent to year 0. At the same time, the High-*Obsolescence* portfolio's obsolescence decreases gradually. Not only does the low-*Obsolescence* portfolio expects to experience an increase in technology obsolescence, but an increase in the conditional volatility of technology obsolescence in the future. In panel (b), we show that the jump of obsolescence volatility is higher for the portfolio of firms that currently have low obsolescence.

As an alternative, we explore the possibility that the asset pricing patterns could be due to mispricing. Prior studies show that stock market can be quite responsive to the arrival of new innovation (Pakes, 1985; Austin, 1993; Hall, Jaffe, and Trajtenberg, 2005; Nicholas, 2008), and that these stock market responses seem to provide a reasonable measure for the value of patents. However, technology obsolescence is a more complex, slow-moving, and less attention-grabbing process. These features may not be fully incorporated in the asset market and thus may lead to mispricing.

We test whether investors form incorrect beliefs about future profitability of firms with different technology obsolescence. For example, technology obsolescence would predict poorer stock returns in the future if investors cannot fully incorporate the poor future performance of the high-*Obsolescence* portfolio. We test this hypothesis by examining whether the abnormal returns mainly accumulate during the earnings announcement dates, similar to Engelberg, McLean, and Pontiff (2018). The returns on those earning news days are only mildly important, explaining 22 percent of the abnormal return. We also found very mild results when investigating the incorrect expectations using I/B/E/S analyst forecast data following Bouchaud et al. (2019).

Next, mispricing could originate from investors' preference over those low-*Obsolescence* stocks, such lower returns. One of the leading models in this stream is Barberis, Jin, and Wang (Forthcoming). In this model, investors have a utility function based on prospect theory. Under this framework, the preference for skewness and high capital-gain-overhang (CGO) can explain a large set of stock market anomalies. In our setting, we do find that the low- and high-*Obsolescence* portfolios fit the logic—the low-*Obsolescence* portfolio, which generates a low return, does have higher skewness and lower CGO. However, a quantitative analysis of the model shows that this could only explain roughly 5–10 percent of the abnormal returns found in our analysis.[17]

5. Final Remarks: Disclosing Some Failed Attempts

So far, the paper has described the method to construct the measure of *Technology Obsolescence*, and established its connection to firm growth and productivity, stock market implications, as well as the power to explain aggregate growth. In this concluding remark, we would like to share what we think are the key missing pieces of the current work, our failed attempts in making progress in those places, and our suggestions for future work.

The one of the key missing pieces is to trace down the sources of firm-level technology obsolescence. Doing so will require us to obtain a better understanding of the detailed network of replacement—of the kind A was replaced by A', then A' replaced by A'', and this goes on. The goal seems very straight-forward, but the execution faces a lot of challenges for a large scale. We tried to use citation network, keywords, patent categorization coding, as well as textual analysis to achieve this goal, but the progress was quite limited.

Due to the limited space, the paper does not fully explore the potential of the measure in asset pricing. Future researchers in the field could potentially use this measure to explore the inter-connection between technology evolution and stock prices—but at the aggregate level and at the cross-section.

[17]We thank Nick Barberis, Lawrence Jin, and Baolian Wang for help with performing the quantitative evaluation using their model.

Appendix. Key Variable Definitions

Variable	Definition and Construction
A. Innovation variables	
Obsolescence	The variable is constructed as the changes in the number of citations received by a firm's predetermined knowledge space. Formally defined by Equation (1) in the paper.
Citation-Weighted Patents	Citation-weighted patents equals to the sum of one plus scaled citations received by all the patents that were granted to that firm. Formally, $$Citation\text{-}Weighted\ Patents_{f,t} = \frac{\sum_{j \in P_{f,t}} (1 + \frac{C_j}{\hat{C}_j})}{B_{f,t}},$$ where C_j is the forward citations received by patent j, and $\hat{C}_j$ is the average number of forward citations received by the patents that were granted in the same year as patent j. $P_{f,t}$ includes all the patents that were granted to that firm f in year t, and $B_{f,t}$ is book assets.
Patent Value	Patent value equals to the sum of all the values of patents that were granted to that firm, scaled by book assets. The value of each patent is calculated with the stock market response to news about patents using the methodology in Kogan et al. (2017).
Competitors' Citation-Weighted Patents	The variable is measured as the weighted average of the citation-weighted patents of its competitors which defined as all the firms in the same industry (SIC3 level) excluding firm itself, scaled by book assets. Formally in Kogan et al. (2017).
Competitors' Patent Value	The variable is measured as the weighted average of the patent value of its competitors which defined as all the firms in the same industry (SIC3 level) excluding firm itself, scaled by book assets. Formally in Kogan et al. (2017).
Patent Number	Number of patent applications filed by a firm in a given year. The natural logarithm of this variable plus one is used in the paper, that is, $\ln(Patent\ Number + 1)$.
Avg. Citations Per Patent	Average citations received by the patents applied by a firms in a given year. The natural logarithm of this variable plus one is used in the paper, that is, $\ln(Avg.\ Citations\ Per\ Patent\ +\ 1)$.
B. Firm characteristics	
Profits	Compustat item sale minus Compustat item cogs, deflated by the CPI.
Output	Nominal value of output. Compustat item sale plus change in inventories Compustat item invt, deflated by the CPI.
Capital	Capital stock. COMPUTAT item ppegt, deflated by the NIPA price of equipment.
Labor	Number of employees. Compustat item emp
TFP	Revenue-based productivity. It is constructed based on the methodology of Olley and Pakes (1996) using the procedure in İmrohoroğlu and Tüzel (2014).

Variable	Definition and Construction
R&D	Research and development expenses (Compustat item xrd), scaled by book assets (Compustat item at).
Idiosyncratic Volatility	Realized mean idiosyncratic squared returns. Firm's idiosyncratic return is defined as the firm's return minus the return on the market portfolio.
C. Other firm characteristics uesed in asset pricing implications	
Size	The natural logarithm of market capitalization at the end of year $t-1$.
log(BM)	The natural logarithm of book value of the common equity to scaled by market value of common equity at the end of year $t-1$.
$Ret(-1,0)$	The monthly returns in the prior month.
$Ret(-12,-2)$	The previous eleven-month returns (with a one-month gap between the holding period and the current month).
SUE	Unexpected quarterly earnings scaled by fiscal-quarter-end market capitalization. Unexpected earnings is I/B/E/S actual earnings minus median forecasted earnings if available, else it is the seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file.
Patents/Assets	The number of patents granted to that firm in year $t-1$ scaled by the firm's book assets at the end of year $t-1$.
R&D/Market Equity	The R&D expenses in fiscal year ending in year $t-1$ scaled by market capitalization at the end of year $t-1$.
Innovation Originality	Innovation originality measure defined in Hirshleifer, Hsu, and Li (2018) in year $t-1$.
Citations-based Innovative Efficiency	The natural logarithm of one plus the citations-based innovative efficiency in year $t-1$, defined in Hirshleifer, Hsu, and Li (2013).
Patents-based Innovative Efficiency	The natural logarithm of one plus the patents-based innovative efficiency in year $t-1$, defined in Hirshleifer, Hsu, and Li (2013).

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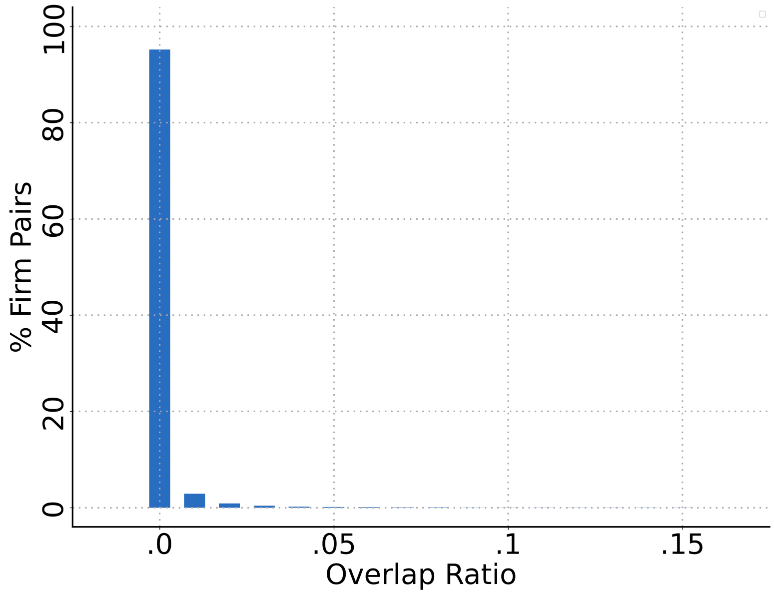
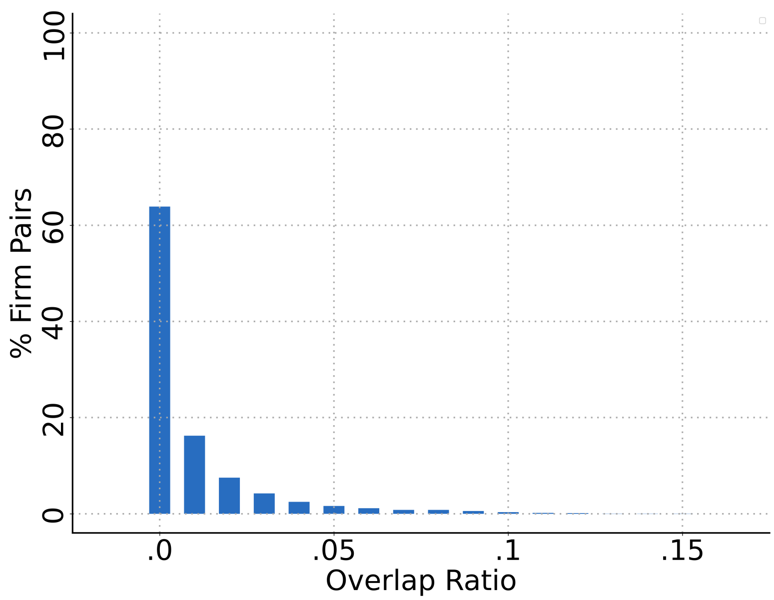


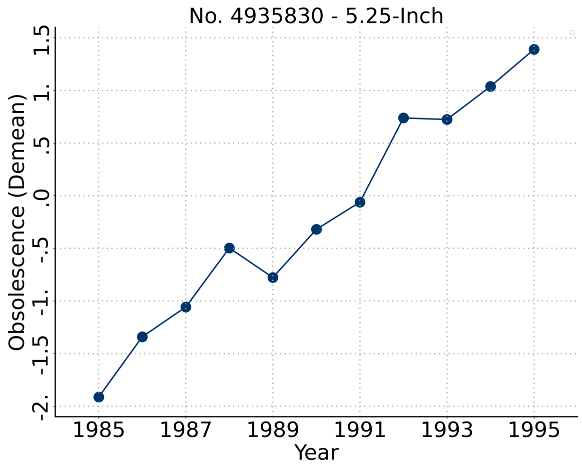
(a) All Firms with Patents



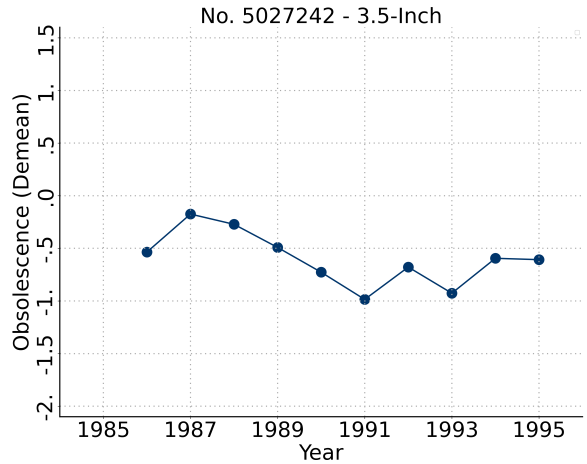
(b) Firms with > 100 Patents

Figure 1. Overlap Ratio of Technology Base Between Within-Industry Firms

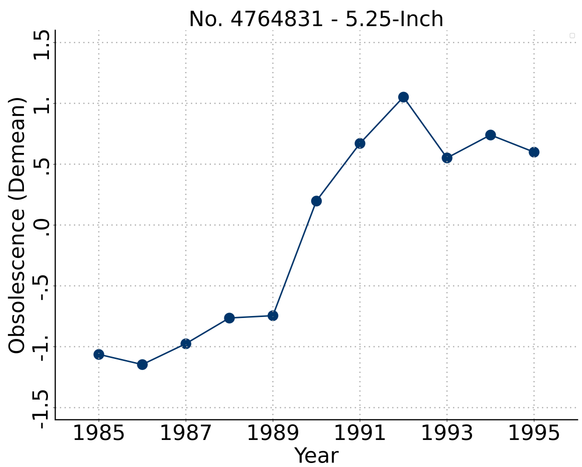
Notes. This figure plots the pair-wise overlap of technology bases among firms in the same SIC3 industry-year. The overlap of a firm i and j's bases are calculated as the size of their intersections and the size of their unions. Panel (a) uses all firms with a patent, while panel (b) focuses on firms with at least 100 patents.



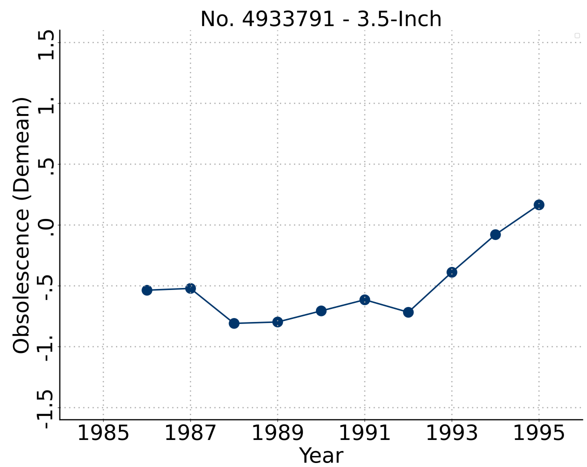
(a) 5.25-inch, US 4935830



(b) 3.5-inch, US 5027242



(c) 5.25-inch, US 4764831



(d) 3.5-inch, US 4933791

Figure 2. Obsolescence of Example HDD Patents

Notes. This figure plots the obsolescence measure for example HDD patents.

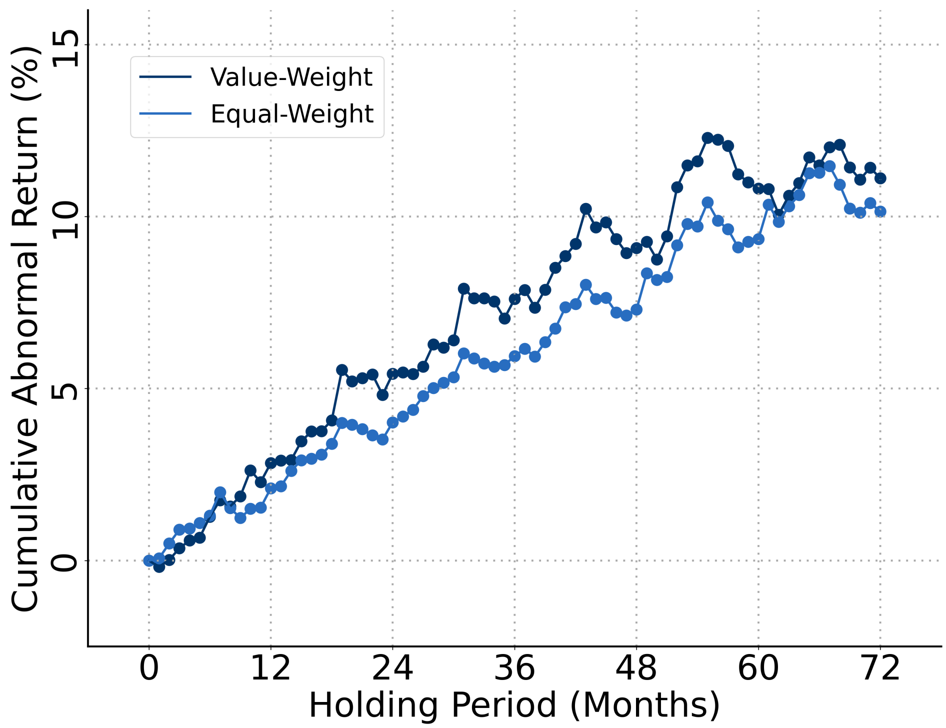
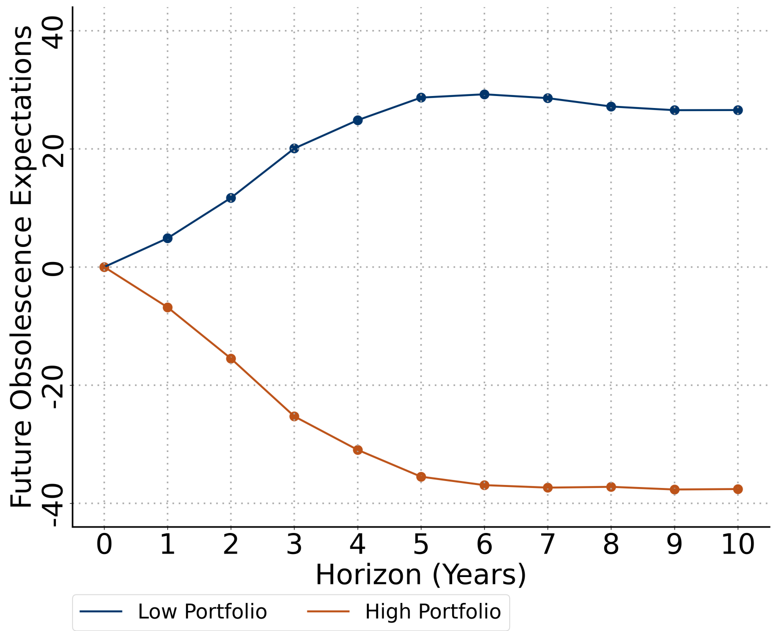
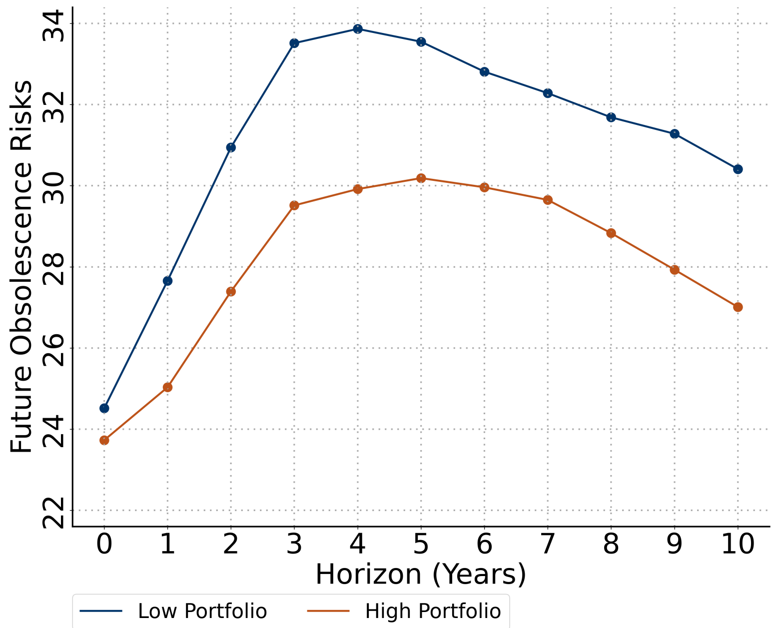


Figure 3. Return to Low-Minus-High *Obsolescence* Portfolio, Event-Time Abnormal Returns

Notes. This figure shows size-B/M-Mom-adjusted cumulative abnormal returns to the low-minus-high Obsolescence portfolios for 60 months following formation. Details of the portfolio construction is described in Section 4.2 of the main text.



(a) Average Future Technology Obsolescence



(b) Volatility of Future Technology Obsolescence

Figure 4. Realized *Obsolescence* and Future *Obsolescence* Risks

Notes. This figure shows future obsolescence of firms sorted based on the current realized obsolescence (panel (a)), and the conditional volatility of technology obsolescence of those portfolios (panel (b)). Details of the portfolio construction is described in Section 4.2 of the main text.

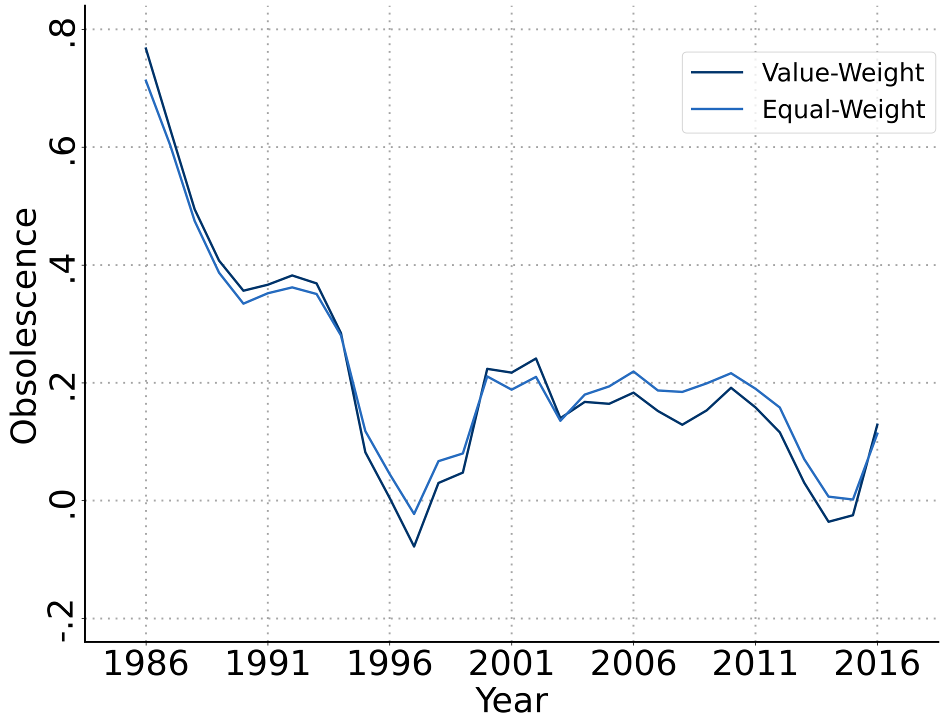
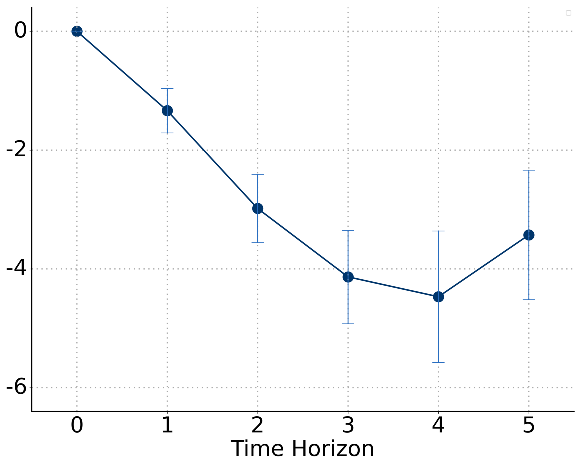
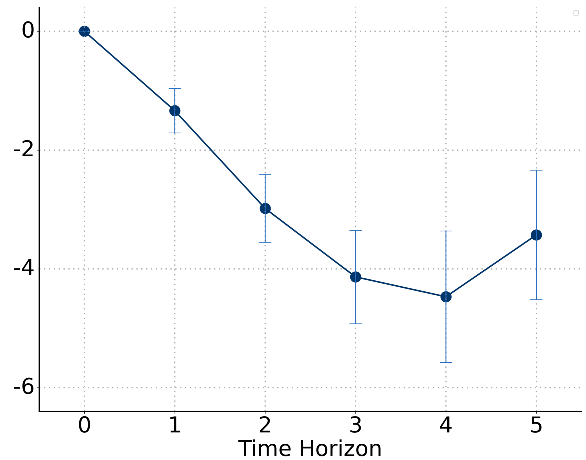


Figure 5. Obsolescence Index, 1986–2016

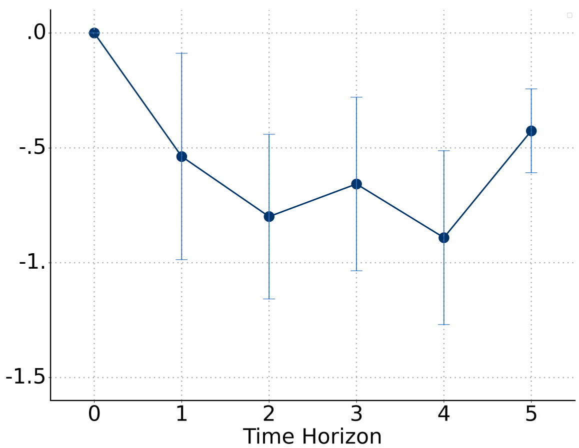
Notes. This figure plots the time series of the obsolescence index, both value-weighted and equal-weighted, as defined in equation (6) in the paper.



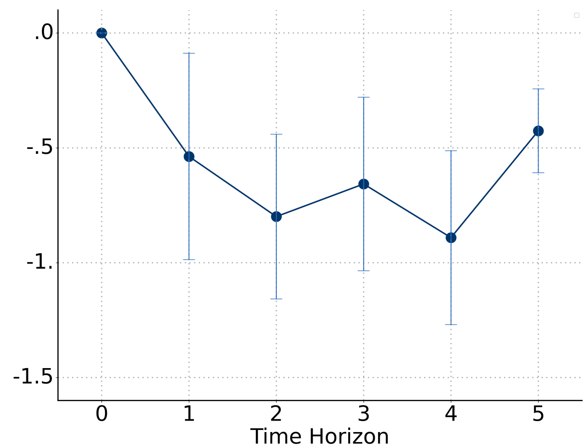
(a) Output ∼ Obsolescence Index (VW)



(b) Output ∼ Obsolescence Index (EW)



(c) TFP ∼ Obsolescence Index (VW)



(d) TFP ∼ Obsolescence Index (EW)

Figure 6. Obsolescence Index and Aggregate Growth

Notes. This figure shows the estimated response of output per capita and productivity to obsolescence using model (7) in the paper. We represent the estimates and the 95% confidence intervals using Newey-West standard errors with maximum lag length equal to 2 plus the horizon. Productivity is utilization-adjusted TFP from Basu, Fernald, and Kimball (2006). Output is GDP (NIPA Table 1.1.5) divided by the consumption price index (St. Louis Fed, CPIAUCNS). Output per capita is computed using population from the U.S. Census Bureau.

Table 1. Firm-Year Level Summary Statistics

	count	mean	std	10%	25%	50%	75%	90%
Obsolescence, Horizon $\omega = 1$ (%)	32697	7.843	13.384	-8.039	-0.414	7.438	15.667	24.201
Obsolescence, Horizon $\omega = 3$ (%)	32697	12.900	26.557	-19.860	-3.336	13.346	29.456	44.765
Obsolescence, Horizon $\omega = 5$ (%)	32697	19.390	34.965	-22.924	-1.626	19.065	40.465	62.388
Obsolescence, Horizon $\omega = 10$ (%)	30644	34.126	51.844	-28.776	0.867	32.694	65.796	100.857
Stock Market-Based Patent Value (SM) (%)	32697	15.322	33.402	0.000	0.251	3.699	15.612	41.488
Citation-Weighted Patents (CW) (%)	32697	7.788	20.317	0.000	0.095	1.484	5.926	17.737
Competitors' Patent Value (%)	31107	26.301	32.828	1.397	6.466	18.629	32.218	51.627
Competitors' Citation-Weighted Patents (%)	31107	3.027	2.684	0.227	0.786	2.135	4.718	7.111

Notes. This table summarizes firm innovation characteristics. *Obsolescence* measure are defined in equation (1), and we report the measures with four different ω parameters, $\omega = 1, 3, 5, 10$. Stock market-based patent value is based on Kogan, Papanikolaou, Seru, and Stoffman (2017), capturing the stock market reactions to new patent approval. Citation-weighted patent counts (CW) is the total forward citation received by patents that a firm applies and subsequently received in each year. Competitors' SM and CW are based on the leave-me-out ratio of the SM and CW measure of firms in the same SIC3 industry in the same year. Variables are winsorized at 1% and 99% using annual breakpoints.

Table 2. Decomposition of the *Obsolescence* Measure

	Decomposition (1)		Decomposition (2)	
	Variation	% of total variation	Variation	% of total variation
Total	3,869.92	100	3,869.92	100
Between industries	385.01	9.95	385.01	9.95
Within industries	1,087.92	28.11	1,126	29.10
Within firm	2,397	61.94		
Within industries × year			2,358.92	60.96

Notes. This table shows variation of *Obsolescence* (denoted as *Obs* here) measure from different sources. The first decomposition decomposes *Obsolescence* into across-industry, across firms within an industry, and within a firm (over time):

$$\begin{aligned}
\textstyle\sum_i \sum_j \sum_t \left(Obs_{ijt} - \overline{\overline{\overline{Obs}}}\right)^2 &= \textstyle\sum_i \sum_j \sum_t \left[(Obs_{ijt} - \overline{Obs}_{ij\cdot}) + (\overline{Obs}_{ij\cdot} - \overline{\overline{Obs}}_{\cdot j\cdot}) + (\overline{\overline{Obs}}_{\cdot j\cdot} - \overline{\overline{\overline{Obs}}})\right]^2 \\
&= \textstyle\sum_i \sum_j \sum_t \left(Obs_{ijt} - \overline{Obs}_{ij\cdot}\right)^2 \quad \text{within firm} \\
&= \textstyle\sum_i \sum_j \sum_t \left(\overline{Obs}_{ij\cdot} - \overline{\overline{Obs}}_{\cdot j\cdot}\right)^2 \quad \text{within industries} \\
&= \textstyle\sum_i \sum_j \sum_t \left(\overline{\overline{Obs}}_{\cdot j\cdot} - \overline{\overline{\overline{Obs}}}\right)^2 \quad \text{between industries}
\end{aligned}$$

where Obs_{ijt} is the *Obsolescence* for firm j in industry j in year t, $\overline{Obs}_{ij\cdot}$ is the within-firm mean for firm i, $\overline{\overline{Obs}}_{\cdot j\cdot}$ is the industry mean for industry j, and $\overline{\overline{\overline{Obs}}}$ is the grand mean.

The second decomposition decomposes *Obsolescence* into across across-industry, within-industry across different years, and within industry-year across different firms:

$$\begin{aligned}
\textstyle\sum_i \sum_j \sum_t \left(Obs_{ijt} - \overline{\overline{\overline{Obs}}}\right)^2 &= \textstyle\sum_i \sum_j \sum_t \left[(Obs_{ijt} - \overline{Obs}_{\cdot jt}) + (\overline{Obs}_{\cdot jt} - \overline{\overline{Obs}}_{\cdot j\cdot}) + (\overline{\overline{Obs}}_{\cdot j\cdot} - \overline{\overline{\overline{Obs}}})\right]^2 \\
&= \textstyle\sum_i \sum_j \sum_t \left(Obs_{ijt} - \overline{Obs}_{\cdot jt}\right)^2 \quad \text{within industry} \times \text{year} \\
&= \textstyle\sum_i \sum_j \sum_t \left(\overline{Obs}_{\cdot jt} - \overline{\overline{Obs}}_{\cdot j\cdot}\right)^2 \quad \text{within industries} \\
&= \textstyle\sum_i \sum_j \sum_t \left(\overline{\overline{Obs}}_{\cdot j\cdot} - \overline{\overline{\overline{Obs}}}\right)^2 \quad \text{between industries}
\end{aligned}$$

where $\overline{Obs}_{\cdot jt}$ is the within-industry-year mean for industry j in year t.

Table 3. Sources of Technology Obsolescence

	(1)	(2)	(3)	(4)
Firm's Own New Patent Value	0.161***	0.261***	0.245***	0.306***
	(0.032)	(0.045)	(0.046)	(0.056)
Competitors' Patent Value	0.213**	0.183*	0.040	0.093
	(0.084)	(0.101)	(0.163)	(0.140)
Upstream Effects of Innovation	0.197*	0.247**		
	(0.113)	(0.122)		
Economy-Wide Index of Innovation			3.309**	2.929**
			(1.517)	(1.188)
Industry FE	Yes		Yes	
Firm FE		Yes		Yes
Year FE	Yes	Yes		
Observations	28,442	28,229	28,860	28,651
R^2	0.268	0.504	0.131	0.399

Notes. This table shows the correlation between the *Obsolescence* measure with several potential sources of new innovation, including firm's own new innovation (*Patent Value*), a firm's industry rivals' new technological breakthroughs (*Competitors' Patent Value*), and innovation from outside the boundary of the specific industry (*Economy-Wide Index of Innovation* or *Upstream Effects of Innovation*). The *Patent Value* and *Competitors' Patent Value* is calculated using the average value in the past five years, and *Economy-Wide Index of Innovation* and *Upstream Effects of Innovation* is measured six years ago. *Economy-Wide Index of Innovation* is calculated following Kogan et al. (2017), and *Upstream Effects of Innovation* is calculated in an external network following Acemoglu, Akcigit, and Kerr (2016) except that we use patent value instead of patent number.

Table 4. Firm-Year Level Summary Statistics

	count	mean	std	10%	25%	50%	75%	90%
Profits, Growth Rate (%)	29734	4.132	29.619	-24.287	-6.369	4.575	15.529	32.280
Output, Growth Rate (%)	31261	3.859	31.495	-23.109	-6.019	4.215	14.769	31.487
Capital, Growth Rate (%)	31995	6.173	19.795	-8.377	0.140	5.520	12.547	23.869
Labor, Growth Rate (%)	31654	2.021	21.017	-16.705	-5.214	1.660	9.672	22.314
TFP, Growth Rate (%)	23816	-0.810	25.809	-24.321	-9.866	-0.415	9.179	22.835
Patent Number, Growth Rate (%)	32152	1.559	57.080	-69.315	-28.768	0.000	33.213	69.315
Avg. Citations Per Patent, Growth Rate (%)	23620	-10.620	69.819	-91.570	-43.634	-10.299	22.314	69.315
Patent Value, Growth Rate (%)	32146	0.001	19.630	-8.860	-1.820	0.000	1.881	8.719
R&D, Growth Rate (%)	27162	-0.389	33.772	-34.098	-12.847	0.388	13.456	33.510
Profits	32689	2190.551	5878.533	7.211	48.198	260.424	1269.023	5200.971
Output	32290	6285.039	16637.534	27.631	132.315	723.575	3759.987	15723.396
Capital	32596	4388.214	15874.031	11.279	44.204	259.103	1774.540	8185.197
Labor	32342	17.702	41.084	0.133	0.520	2.867	13.500	47.313
TFP	25055	-0.336	0.448	-0.798	-0.539	-0.332	-0.113	0.165
Patent Number	32697	43.560	144.593	0.000	1.000	5.000	19.000	82.000
Avg. Citations Per Patent	26196	23.274	33.025	2.000	5.750	13.645	26.200	51.286
R&D	32694	0.082	0.129	0.000	0.009	0.037	0.101	0.199
Idiosyncratic Volatility	32623	0.001	0.002	0.000	0.000	0.001	0.001	0.003

Notes. This table summarizes firm characteristics at the firm-year level. We report the growth rate and raw values of the following variables: Profits is firm gross profits (Compustat item sale minus Compustat item cogs, deflated by the CPI); Output is the nominal value of firm output (Compustat item sale plus change in inventories Compustat item invt, deflated by the CPI); Capital is firm capital stock (Compustat item ppegt, deflated by the NIPA price of equipment); Labor is the number of employees (Compustat item emp); Patent Number is the natural logarithm of one plus the number of patent applications filed by the firm for the year (noting the right truncation problem); Avg. Citations Per Patent is the natural logarithm of one plus average citations received by the patents applied by the firm for the year; Patent Value is the sum of all the values of patents that were granted to that firm, scaled by book assets (Compustat item at), which is constructed using the methodology in KPSS; R&D is the research and development expenses (Compustat item xrd), scaled by book assets (Compustat item at). Idiosyncratic Volatility is the realized mean idiosyncratic squared returns, where firm's idiosyncratic return is defined as the firm's return minus the return on the market portfolio. Detailed variable definitions are provided in the Appendix. Variables are winsorized at 1% and 99% using annual breakpoints.

Table 5. Technology Obsolescence and Firm Growth

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.009***	-0.012***	-0.014**	-0.017**	-0.021**
	(0.003)	(0.004)	(0.006)	(0.008)	(0.011)
			Output		
$Obsolescence_t$	-0.009***	-0.014***	-0.017**	-0.020**	-0.025**
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
			Capital		
$Obsolescence_t$	-0.010***	-0.020***	-0.029***	-0.038***	-0.045***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.012)
			Labor		
$Obsolescence_t$	-0.005**	-0.010**	-0.014**	-0.015*	-0.015
	(0.002)	(0.004)	(0.007)	(0.008)	(0.010)
			TFP		
$Obsolescence_t$	-0.007**	-0.010***	-0.011***	-0.013**	-0.011*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity using the model below (equation (2)) in the paper):

$$\log Y_{f,t+\tau} - \log Y_{f,t} = \beta_\tau \cdot Obsolescence_{f,t} + \theta_\tau \cdot X_{f,t} + \delta_{I\times t} + \varepsilon_{f,t+\tau}.$$

The outcome variables, Y, include firm profits, output, capital, employment, and TFPR, all defined and described in Table 4. The table presents results estimated using up to five years from t. Controls include one-period lag of the dependent variable, log values of firm capital, employment, and the firm's idiosyncratic volatility. All right-hand-side variables are standardized to unit standard deviation to facilitate magnitude interpretations. The model includes industry (SIC3)-by-year fixed effects. Standard errors are clustered by firm and year, and they are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Technology Obsolescence and Growth, Controlling For Innovation Measures

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.008***	-0.011***	-0.013**	-0.015*	-0.018*
	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	0.001	0.001	0.003	0.008	0.023
	(0.005)	(0.008)	(0.012)	(0.015)	(0.017)
$Patent\ Value_t$ (SM)	0.024***	0.036***	0.046***	0.052***	0.059***
	(0.007)	(0.012)	(0.016)	(0.018)	(0.018)
			Output		
$Obsolescence_t$	-0.008***	-0.013***	-0.016**	-0.019*	-0.023*
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.005	-0.008	-0.016	-0.014	-0.008
	(0.004)	(0.007)	(0.010)	(0.013)	(0.015)
$Patent\ Value_t$ (SM)	0.020***	0.033***	0.043***	0.050**	0.055***
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
$Obsolescence_t$	-0.010***	-0.019***	-0.028***	-0.037***	-0.044***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.012)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.009***	-0.012***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.011)
$Patent\ Value_t$ (SM)	0.019***	0.034***	0.042***	0.048***	0.054***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.017)
			Labor		
$Obsolescence_t$	-0.005**	-0.010**	-0.013**	-0.014	-0.014
	(0.002)	(0.004)	(0.007)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006**	-0.009*	-0.011	-0.012	-0.011
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$ (SM)	0.013***	0.022***	0.028***	0.033***	0.036***
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
			TFP		
$Obsolescence_t$	-0.007**	-0.009**	-0.010**	-0.012**	-0.010
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
$Citation\text{-}Weighted\ Patents_t$ (CW)	0.000	0.008	0.009	0.006	0.013
	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)
$Patent\ Value_t$ (SM)	0.017**	0.024*	0.029**	0.035***	0.039***
	(0.008)	(0.013)	(0.012)	(0.011)	(0.010)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity after adding measures of new innovation, the stock market-based patent value from Kogan et al. (2017) and citation-weight patent counts. The design follows that in Table 5.

Table 7. Heterogeneity Across Different Firm and Industry Characteristics

Heterogeneity	Core Patents		Product/Process Patents		Competition	
	Core	Non-Core	Product	Process	High	Low
			Profits			
$Obsolescence_t$	-0.012*	-0.001	-0.015**	-0.004	-0.015**	-0.012
	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)	(0.014)
			Output			
$Obsolescence_t$	-0.016**	-0.002	-0.017**	-0.008	-0.021**	-0.005
	(0.007)	(0.007)	(0.008)	(0.005)	(0.009)	(0.012)
			Capital			
$Obsolescence_t$	-0.026***	-0.012**	-0.030***	-0.010*	-0.036***	-0.001
	(0.007)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
			Labor			
$Obsolescence_t$	-0.011*	-0.006	-0.016**	-0.004	-0.018**	0.004
	(0.006)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
			TFP			
$Obsolescence_t$	-0.010**	-0.005	-0.011***	-0.006	-0.013**	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity in different subsamples. The core vs. non-core (peripheral) patents are defined as the top technology class(es) that populate 50% of the firm's all patents. The product (disembodied) vs. process (embodied) innovation is defined using the textual description of patents based on Bena and Simintzi (2019). The product market competition is categorized into high vs. low based on the SIC3 HHI. The empirical design follows that in Table 5, only the $t + 3$ horizon is reported.

Table 8. Technology Obsolescence and Competitor Innovation Measures

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.008***	-0.010**	-0.013*	-0.016*	-0.022*
	(0.003)	(0.004)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$	0.023***	0.034***	0.044***	0.052***	0.062***
	(0.007)	(0.011)	(0.015)	(0.016)	(0.017)
$Competitors'\ Patent\ Value_t$	-0.005	-0.021	-0.030	-0.033	-0.036
	(0.014)	(0.022)	(0.030)	(0.039)	(0.046)
			Output		
$Obsolescence_t$	-0.008**	-0.013***	-0.016**	-0.018*	-0.022*
	(0.003)	(0.005)	(0.008)	(0.011)	(0.014)
$Patent\ Value_t$	0.017***	0.028**	0.034***	0.042**	0.048***
	(0.006)	(0.011)	(0.013)	(0.019)	(0.018)
$Competitors'\ Patent\ Value_t$	-0.012	-0.026	-0.042	-0.059	-0.073
	(0.016)	(0.025)	(0.031)	(0.043)	(0.046)
			Capital		
$Obsolescence_t$	-0.009***	-0.018***	-0.028***	-0.037***	-0.046***
	(0.002)	(0.005)	(0.008)	(0.010)	(0.013)
$Patent\ Value_t$	0.015***	0.027***	0.034***	0.040***	0.044***
	(0.003)	(0.007)	(0.010)	(0.013)	(0.015)
$Competitors'\ Patent\ Value_t$	-0.015	-0.030	-0.055*	-0.070*	-0.087*
	(0.011)	(0.020)	(0.030)	(0.039)	(0.047)
			Labor		
$Obsolescence_t$	-0.005**	-0.008*	-0.011*	-0.013	-0.013
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
$Patent\ Value_t$	0.010***	0.017***	0.021***	0.025**	0.028**
	(0.003)	(0.006)	(0.008)	(0.010)	(0.012)
$Competitors'\ Patent\ Value_t$	-0.013*	-0.029*	-0.054**	-0.069*	-0.079*
	(0.008)	(0.016)	(0.026)	(0.035)	(0.043)
			TFP		
$Obsolescence_t$	-0.006**	-0.011***	-0.012**	-0.014**	-0.012*
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
$Patent\ Value_t$	0.015*	0.023*	0.028**	0.034***	0.039***
	(0.008)	(0.013)	(0.012)	(0.012)	(0.011)
$Competitors'\ Patent\ Value_t$	-0.025**	-0.037*	-0.036**	-0.031	-0.028
	(0.013)	(0.020)	(0.017)	(0.025)	(0.027)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity after adding competitors' innovation value (the stock market-based patent value from KPSS), which is defined as the value of patents created by firms in the same SIC3 industry except the focal firm itself. The design follows that in Table 5.

Table 9. Aggregation Impact of Technology Obsolescence

Time Horizon	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$
			Profits		
G_τ (%)	-0.566	-0.418	-0.326	-0.308	-0.311
g_τ (%)	3.349	3.313	3.248	3.362	3.460
G/g (%)	-16.907	-12.624	-10.047	-9.178	-8.995
			Output		
G_τ (%)	-0.606	-0.502	-0.407	-0.367	-0.386
g_τ (%)	2.675	2.612	2.587	2.684	2.744
G/g (%)	-22.657	-19.204	-15.715	-13.670	-14.047
			Capital		
G_τ (%)	-0.784	-0.765	-0.750	-0.765	-0.762
g_τ (%)	4.956	4.960	4.924	5.072	5.232
G/g (%)	-15.812	-15.423	-15.225	-15.091	-14.559
			Labor		
G_τ (%)	-0.362	-0.365	-0.339	-0.266	-0.220
g_τ (%)	0.889	1.005	0.984	0.921	0.884
G/g (%)	-40.691	-36.296	-34.444	-28.918	-24.882

Notes. This table reports the estimate of G_τ and g_τ for growth outcomes including Profits, Output, Capital, and Labor, for $\tau = 1, 2, ..., 5$. We also report the ratio of the two. All the numbers are reported in percentages. G and g are defined in Equations (4) and (5) in the main text.

Table 10. Return Predictive Power of Technology Obsolescence

Panel (a): Value-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.889***	0.388***	0.384***	0.413***	0.336***	0.423***	0.410***	0.444***
	(0.265)	(0.084)	(0.083)	(0.085)	(0.093)	(0.093)	(0.093)	(0.092)
Middle	0.639***	0.065	0.108	0.007	-0.100	0.040	0.078	0.028
	(0.240)	(0.065)	(0.068)	(0.067)	(0.079)	(0.069)	(0.073)	(0.068)
High	0.587**	-0.029	0.027	-0.157	-0.194*	-0.082	-0.024	-0.144
	(0.238)	(0.102)	(0.103)	(0.096)	(0.111)	(0.101)	(0.105)	(0.097)
Low–High	0.302*	0.418***	0.357**	0.570***	0.530***	0.505***	0.434***	0.588***
	(0.172)	(0.147)	(0.147)	(0.145)	(0.157)	(0.151)	(0.156)	(0.147)

Panel (b): Equal-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.925***	0.242**	0.378***	0.375***	0.332***	0.200**	0.344***	0.372***
	(0.326)	(0.096)	(0.094)	(0.089)	(0.109)	(0.094)	(0.094)	(0.090)
Middle	0.899***	0.167*	0.309***	0.197**	0.144	0.082	0.228**	0.190**
	(0.318)	(0.099)	(0.090)	(0.083)	(0.111)	(0.094)	(0.089)	(0.085)
High	0.757**	-0.032	0.141	0.087	0.031	-0.109	0.078	0.072
	(0.356)	(0.109)	(0.104)	(0.094)	(0.112)	(0.111)	(0.110)	(0.096)
Low–High	0.168*	0.274***	0.237***	0.288***	0.301***	0.310***	0.266***	0.301***
	(0.093)	(0.079)	(0.082)	(0.080)	(0.085)	(0.086)	(0.090)	(0.083)

Panel (c): Value-Weight Portfolios' Four-Factor Loadings

	MKT	SMB	HML	UMD
Low	0.971***	-0.053*	-0.344***	0.005
	(0.022)	(0.032)	(0.030)	(0.024)
Middle	0.969***	-0.132***	-0.068**	-0.055**
	(0.028)	(0.023)	(0.026)	(0.026)
High	0.942***	-0.031	0.153**	-0.073*
	(0.031)	(0.042)	(0.065)	(0.039)
Low–High	0.030	-0.022	-0.497***	0.079
	(0.040)	(0.061)	(0.083)	(0.056)

Notes. This table presents monthly portfolio returns (in %) for portfolios sorted on *Obsolescence*. At the end of June of year t from 1986 to 2016, we sort firms based on their obsolescence measure into three portfolios—Low, Middle, High. The Low portfolio contains all stocks below the 30th percentile in *Obsolescence*, and the High portfolio contains all stocks above the 70th percentile. The *Obsolescence* used to form these portfolios are from the prior calendar year $t-1$. Based on our formation of the technology obsolescence, the measure is publicly observable at the end of year $t-1$ and does not incorporate any forward-looking information. We hold these portfolios over the next twelve months, from July of year t to June of year $t+1$. We compute their value-weighted monthly returns and equal-weighted monthly returns. We report the average monthly return in excess of one-month Treasury bill rate (Exret). We also report alphas from the regression of the time-series of portfolio excess returns on various factor models: the Fama-French three factors (3F), the four factors (4F, three factors + UMD/Momentum), 4F + RMW + CMA (robust-minus-weak, conservative-minus-aggressive), the q-Factor model (Hou, Xue, and Zhang, 2015), as well as the factor models that replaces the traditional Fama-French HML factor with the intangible-adjusted HML (Eisfeldt, Kim, and Papanikolaou, 2020). In panel (a) and (b) we report the results for value-weight and equal-weight portfolios, respectively. In panel (c) we report the four-factor loadings of the portfolios. Standard errors are reported in parenthesis.

Table 11. Return Predictive Power of Technology Obsolescence: Fama-MacBeth Regressions

	VWLS				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Obsolescence	-0.187**	-0.216***	-0.196***	-0.121***	-0.067*	-0.080**	-0.082***	-0.067***
	(0.077)	(0.058)	(0.053)	(0.037)	(0.037)	(0.031)	(0.031)	(0.025)
Size		-0.182	-0.159	-0.180*		-0.235***	-0.204**	-0.204**
		(0.119)	(0.116)	(0.103)		(0.076)	(0.079)	(0.080)
$\log(BM)$		0.132*	0.157**	0.132**		0.094*	0.065	0.078*
		(0.078)	(0.075)	(0.064)		(0.048)	(0.046)	(0.042)
$Ret(-1,0)$		-0.376***	-0.405***	-0.444***		-0.532***	-0.552***	-0.611***
		(0.092)	(0.088)	(0.078)		(0.060)	(0.061)	(0.063)
$Ret(-12,-2)$		0.100	0.078	0.071		0.026	-0.000	-0.047
		(0.124)	(0.120)	(0.108)		(0.108)	(0.107)	(0.101)
Idiosyncratic Volatility		-0.510*	-0.608**	-0.537**		-0.446**	-0.554***	-0.565***
		(0.305)	(0.284)	(0.261)		(0.188)	(0.176)	(0.174)
SUE		-0.021	0.015	0.009		0.054	0.051	0.044
		(0.092)	(0.091)	(0.083)		(0.038)	(0.038)	(0.036)
Patents/Assets			0.253*	0.106			0.064	0.029
			(0.147)	(0.115)			(0.063)	(0.055)
R&D/Market Equity			0.120	0.135			0.227***	0.207***
			(0.100)	(0.087)			(0.061)	(0.057)
Innovation Originality			-0.023	0.054			0.022	0.023
			(0.043)	(0.040)			(0.028)	(0.028)
Citations-Based Innovative Efficiency			0.147	0.105			0.099**	0.110***
			(0.114)	(0.094)			(0.039)	(0.037)
Patents-Based Innovative Efficiency			-0.113	-0.067			-0.100**	-0.098***
			(0.096)	(0.090)			(0.040)	(0.038)
Industry fixed effect	No	No	No	Yes	No	No	No	Yes
Observations	298,759	289,919	289,919	289,919	298,759	289,919	289,919	289,919
# firms	829	805	805	805	829	805	805	805
R^2	0.138	0.251	0.283	0.456	0.003	0.069	0.084	0.148

Notes. This table reports the average slopes (in %) and their Newey and West (1987) autocorrelation-adjusted heteroscedasticity-robust standard errors in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions. For each month from July of year t to June of year $t+1$, we regress monthly returns of individual stocks on *Obsolescence* of year $t-1$, different sets of control variables and industry fixed effects. We omit the intercept, the slopes on the 48 industry dummies, and the slopes on the missing dummy and its interactions with all other control variables for brevity. All variables are defined in the appendix. *Obsolescence* measure are defined in equation (1). *Size* is the natural logarithm of market capitalization at the end of year $t-1$. $\log(BM)$ is the natural logarithm of book value of the common equity to scaled by market value of common equity at the end of year $t-1$. $Ret(-1,0)$ is the monthly returns in the prior month. $Ret(-12,-2)$ is the previous eleven-month returns (with a one-month gap between the holding period and the current month. SUE is the unexpected quarterly earnings scaled by fiscal-quarter-end market capitalization, where unexpected earnings is I/B/E/S actual earnings minus median forecasted earnings if available, else it is the seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file. Patents/Assets is the number of patents granted to that firm in year $t-1$ scaled by the firm's book assets at the end of year $t-1$. R&D/Market Equity is the R&D expenses in fiscal year ending in year $t-1$ scaled by market capitalization at the end of year $t-1$. Innovation Originality is the innovation originality measure defined in Hirshleifer, Hsu, and Li (2018) in year $t-1$. Citations-based and Patents-based Innovative Efficiency is the natural logarithm of one plus the citations-based and patents-based innovative efficiency measures in year $t-1$, defined in Hirshleifer, Hsu, and Li (2013). All independent variables are normalized to zero mean and one standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1986 to June of 2016. R-squared (number of firms) is the time-series average of the R-squared (number of firms) from the monthly cross-sectional regressions.

Appendix (For Online Publication Only)

A.1. Using Annual Citations To Capture Technology Evolution

Knowledge itself ages. The scientific value and relevance of a technology usually experiences a hump-shaped dynamic. The scientific relevance would increase in the early years as the new technology starts to diffuse and be adopted; it would later decay as the technology fails to stay at the frontier and be replaced by newer generations of technology. This conceptual idea has been discussed in many classic work in innovation (Pakes and Schankerman, 1984; Caballero and Jaffe, 1993).

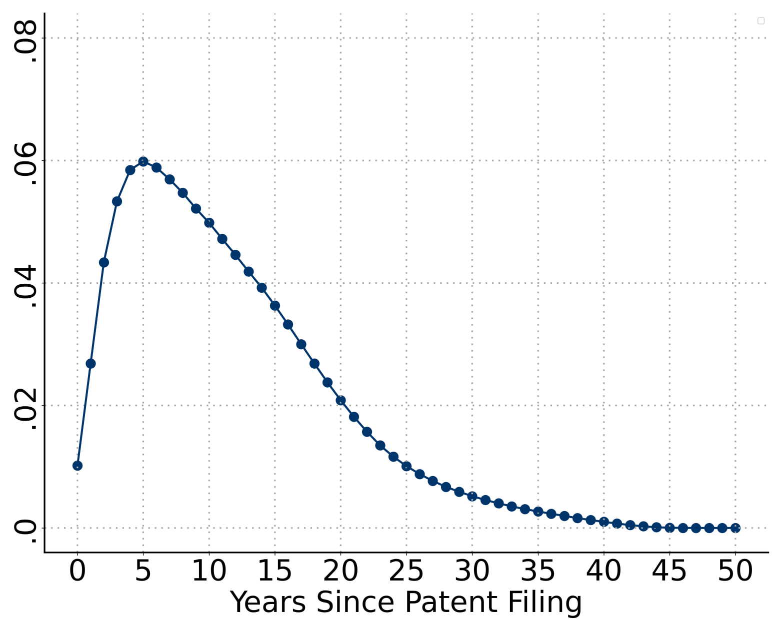
Annual citations received by each patent capture knowledge aging. We start by presenting two motivating facts. In Figure A.1, we plot the age distribution of patents that a new patent cites as its prior art. It shows that new patents rely heavily on patents that are below twenty years old. In fact, half or more of the cited patents in a new technology are within ten years old. A small number of patents have quite long-lasting impact and may be influential even after 50 years, suggesting heterogeneity in the speed of aging.

In Figure A.2, we perform the reverse exercise to show the same point. In panel (a), we study forward citations each patent receives through its life cycle. Because of the right-truncation problem of patent citations, we produce the citation dynamic curve by cohorts of patent filing years. Patents keep obtaining citations even after one or two decades, after the first few years of "climbing up" period. In Figure A.2 panel (b) we show heterogeneity in this citation pattern. In this graph, we divide patents from the same early cohort of 1990 into three groups based on the ratio of firm five years' citations in the total number of citations to date. The early bloomers (orange line) collect significantly more patents in their earlier life than the late-bloomers (dark navy line), but they also age faster.

If we summarize this difference in forward citation dynamics using one statistic, that is the half life of a technology—the time it takes for each patent to collect half of its total citations (Machlup, 1962). The median half lives for the early-bloomer group and the later-bloomer group are 8 years and 17 years, respectively. Figure A.3 shows the distribution of patent-level half lives for the sample of parents granted prior to 2000. We again observe a very robust heterogeneity. The half lives of patents also vary across different industries and across different technology spaces. Figure A.4 shows the half lives of patents summarized by the Fama-French 48 industries, and in Appendix Figure A.5 we show those difference across different technological fields categorized by the International Patent

Classification (IPC).

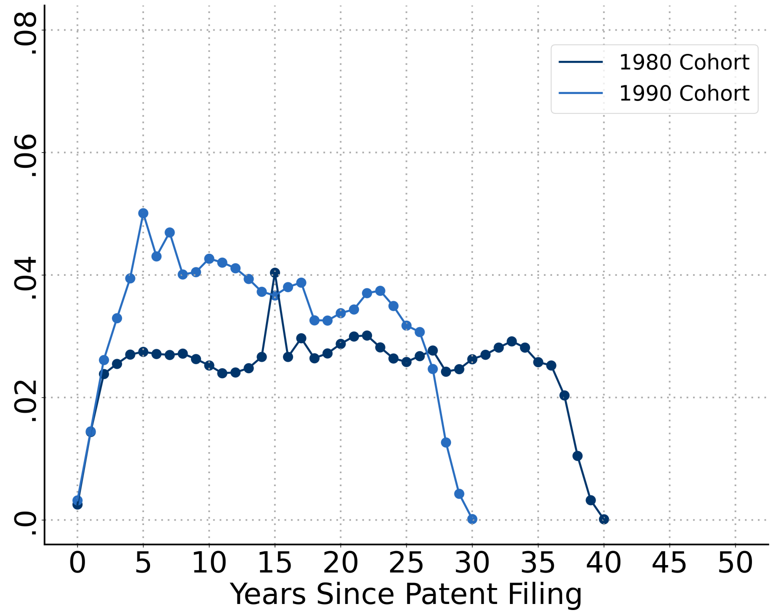
One caveat is that the process of citing patents could be noisy (Roach and Cohen, 2013). Most noticeably, a large portion of citations are so-called examiner-citations, which are inserted by patent examiners but not the patent applicants or their hired professionals (Alcácer, Gittelman, and Sampat, 2009). This could affect both the construction of technology bases and citations they receive. Since the technology obsolescence measure is a within-firm change, those concerns should not introduce too strong of a systematic error into our analysis. Just to make sure this issue does not affect our measure, for post-2002 sample in which we could observe citation sources, i.e. examiner-citations vs. applicant ones, we find the correlation of the two versions of obsolescence with and without examiner patents is 0.94.



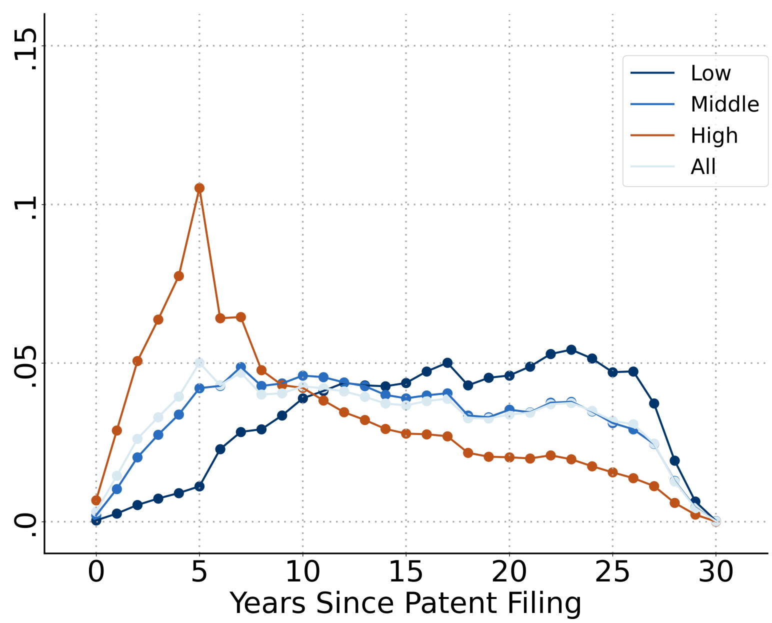
(a) Average Backward Citation Dynamic

Figure A.1. Patent Backward and Forward Citation Dynamics

Notes. This figure plots distributions of backward citation lags. In specific, each data point in the data is a citation pair—the citing patents and the cited. It plots the distribution of the age of the cited patents at the time of the citing patent was applied.



(b) Heterogeneity in Forward Citation Dynamic



(a) Average Backward Citation Dynamic

Figure A.2. Dynamics of Citations Received By Each Patent

Notes. This figure presents the dynamics of citations received by patents and its heterogeneities. Panel (a) presents the annual citation received by patents organized by the 1980 and the 1990 cohort. Panal (b) presents the annual citation received by patents of the 1990 cohort depending on whether they are early- or late-bloomers defined based on the ratio of firm five years' citations in the total number of citations to date. Panel (b) presents the histogram of a patent's half-life using all patents applied and granted before 2000.

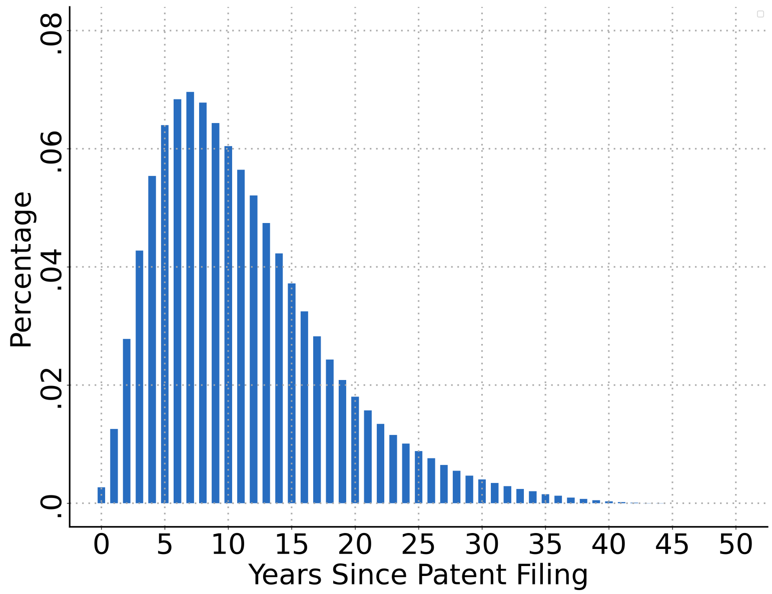


Figure A.3. Distribution of Patents' Half-Lives

Notes. This figure presents the histogram of a patent's half-life using all patents applied and granted before 2000. The half-life is defined as the number of years it takes for a patent to received half of the total citations received by the patent to date.

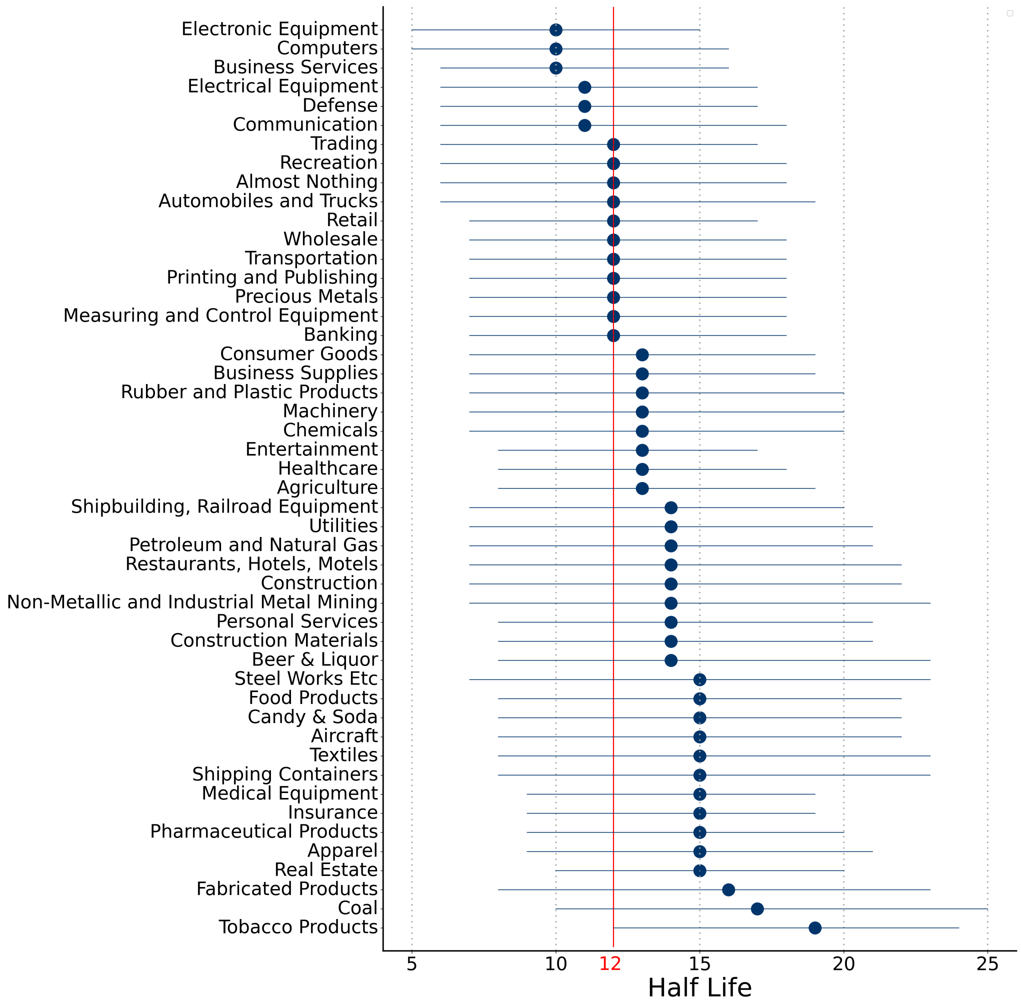


Figure A.4. Dynamics of Citations Received By Each Patent—Heterogeneity

Notes. This figure plots the half-lives of patents produced by firms from different industries. The sample of patents are restricted to pre-2000 cohort to allow adequate time to realize the half-life of patents.

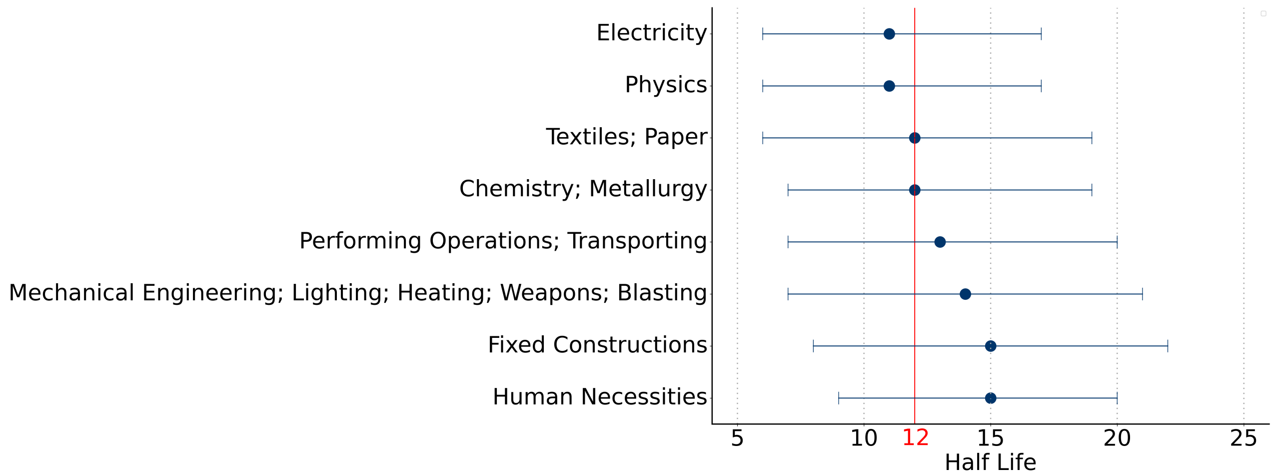


Figure A.5. Patent Citation Half-Lives By International Patent Classification Categories

A.2. Additional Results

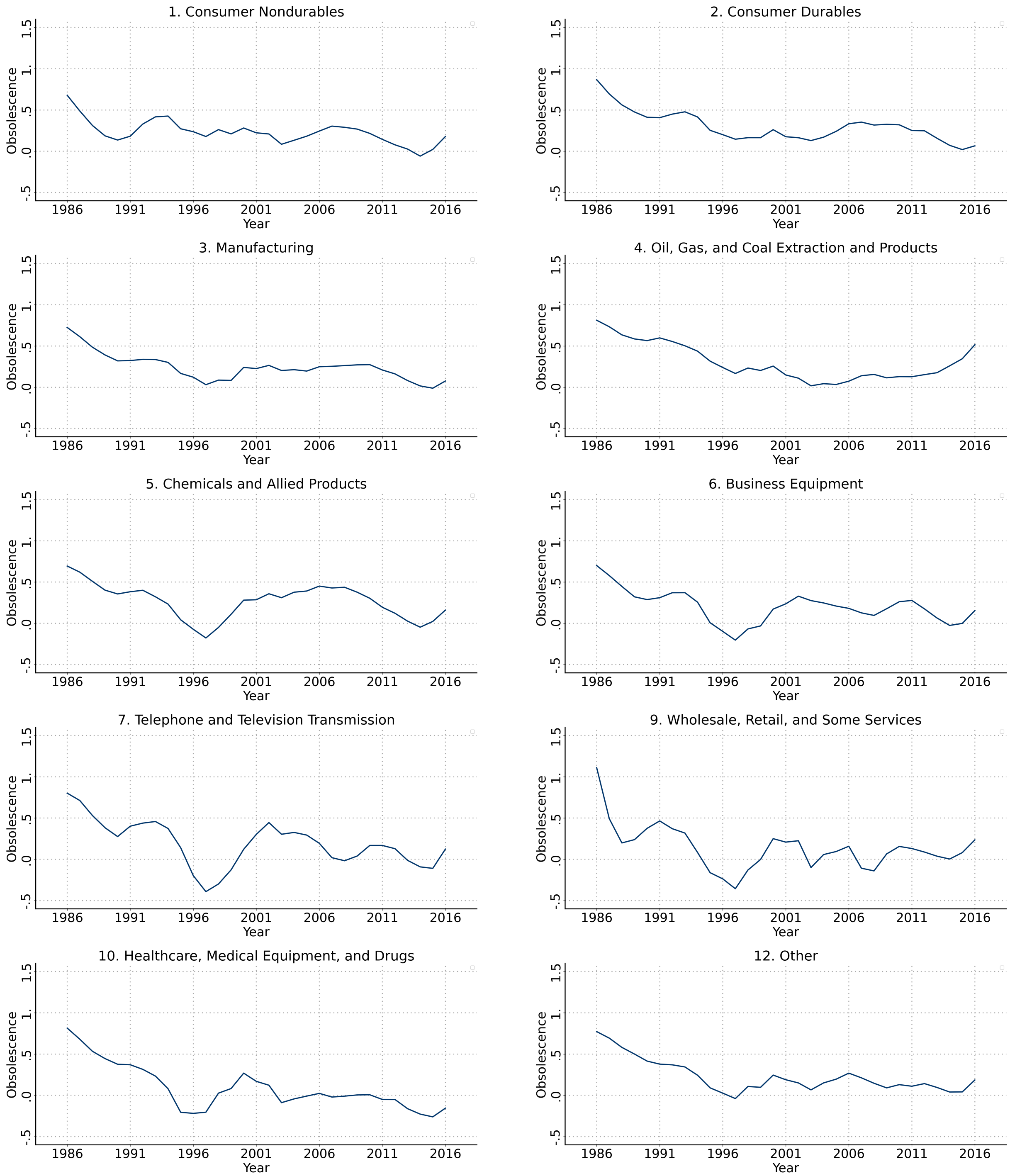


Figure A.6. Obsolescence Index (Value-Weight) By Industry, 1986–2016

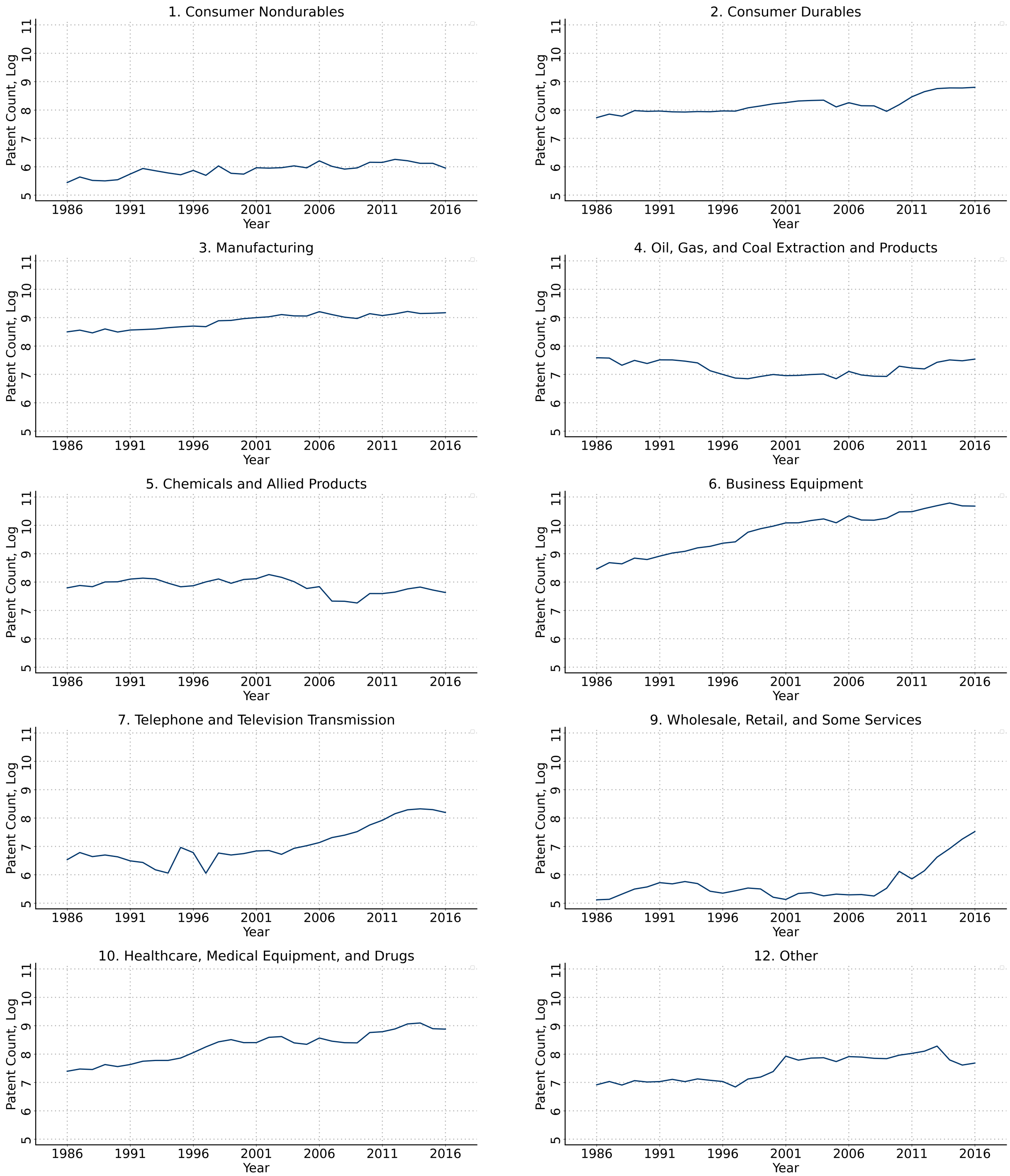


Figure A.7. Patent Counts (Log) By Industry, 1986–2016

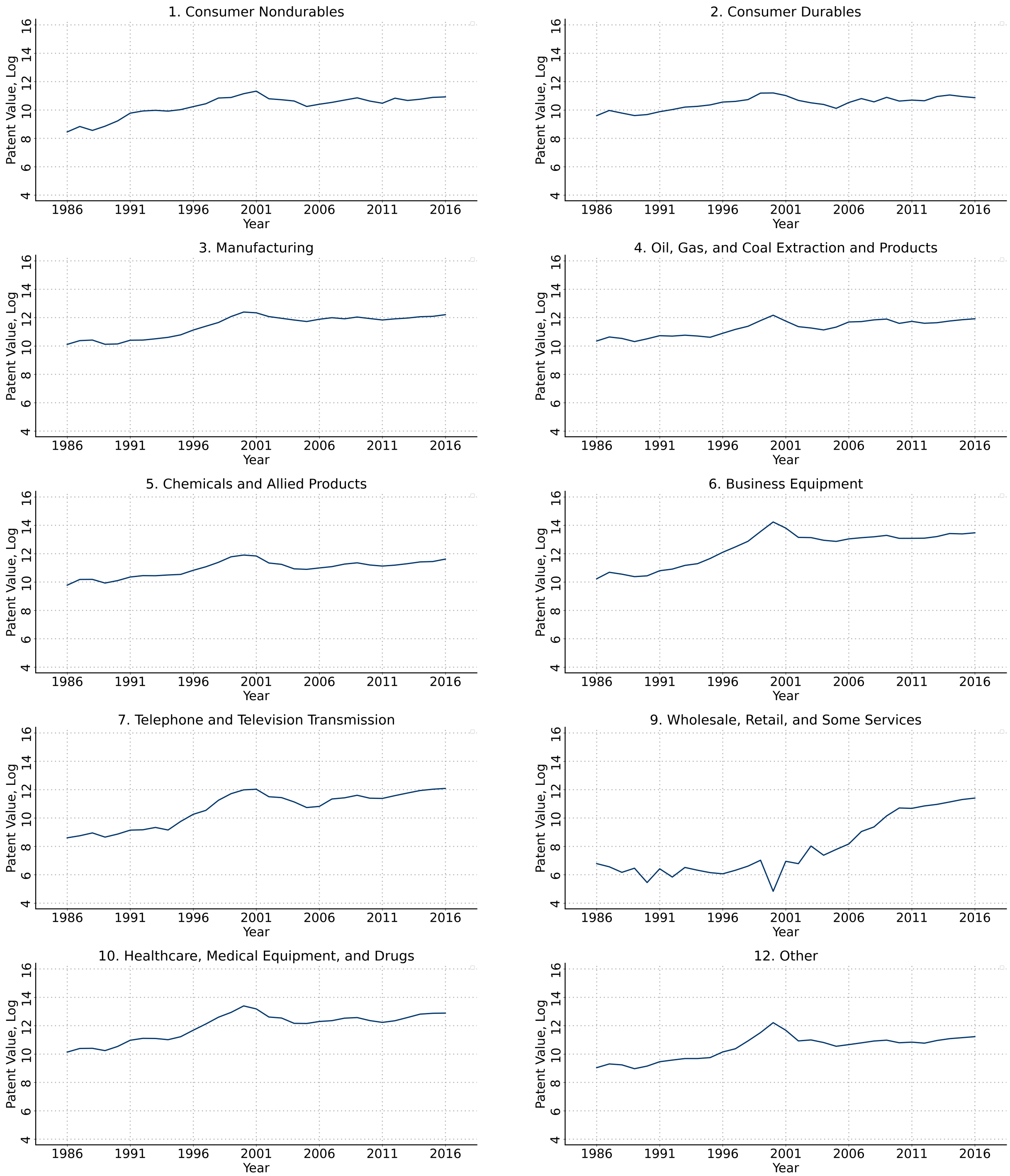


Figure A.8. Patent Value (Log) By Industry, 1986–2016

Table A.1. Robustness of Obsolescence Measure - Horizons $\omega = 1$

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.004	-0.006	-0.012**	-0.014**	-0.016**
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)
$Citation\text{-}Weighted\ Patents_t$	0.002	0.002	0.004	0.009	0.024
	(0.005)	(0.008)	(0.012)	(0.015)	(0.017)
$Patent\ Value_t$	0.024***	0.036***	0.046***	0.053***	0.059***
	(0.007)	(0.012)	(0.016)	(0.018)	(0.018)
			Output		
$Obsolescence_t$	-0.007**	-0.009**	-0.015***	-0.020***	-0.027***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	-0.005	-0.007	-0.015	-0.013	-0.007
	(0.004)	(0.007)	(0.010)	(0.013)	(0.015)
$Patent\ Value_t$	0.020***	0.034***	0.043***	0.050**	0.055***
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
$Obsolescence_t$	-0.008***	-0.013***	-0.016***	-0.022***	-0.030***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	-0.009***	-0.011***	-0.013**	-0.012	-0.012
	(0.002)	(0.004)	(0.006)	(0.008)	(0.011)
$Patent\ Value_t$	0.020***	0.034***	0.043***	0.049***	0.054***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.017)
			Labor		
$Obsolescence_t$	-0.005***	-0.009***	-0.012***	-0.018***	-0.020***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)
$Citation\text{-}Weighted\ Patents_t$	-0.006**	-0.009*	-0.010	-0.011	-0.011
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$	0.013***	0.023***	0.028***	0.033***	0.036***
	(0.003)	(0.007)	(0.010)	(0.012)	(0.014)
			TFP		
$Obsolescence_t$	-0.002	-0.004	-0.006	-0.011***	-0.013***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
$Citation\text{-}Weighted\ Patents_t$	0.001	0.008	0.010	0.007	0.014
	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)
$Patent\ Value_t$	0.017**	0.024*	0.029**	0.035***	0.039***
	(0.008)	(0.013)	(0.012)	(0.011)	(0.010)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity after adding measures of new innovation, the stock market-based patent value from Kogan et al. (2017) and citation-weight patent counts. The design follows that in Table 5.

Table A.2. Robustness of Obsolescence Measure—Horizons $\omega = 3$

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.006**	-0.011***	-0.014**	-0.016**	-0.016*
	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	0.002	0.002	0.003	0.008	0.024
	(0.005)	(0.008)	(0.012)	(0.015)	(0.017)
$Patent\ Value_t$	0.024***	0.036***	0.046***	0.053***	0.059***
	(0.007)	(0.012)	(0.016)	(0.018)	(0.018)
			Output		
$Obsolescence_t$	-0.006**	-0.011***	-0.018**	-0.021**	-0.024**
	(0.003)	(0.004)	(0.007)	(0.009)	(0.010)
$Citation\text{-}Weighted\ Patents_t$	-0.005	-0.008	-0.016	-0.014	-0.007
	(0.004)	(0.007)	(0.010)	(0.013)	(0.015)
$Patent\ Value_t$	0.020***	0.033***	0.043***	0.050**	0.055***
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
$Obsolescence_t$	-0.009***	-0.015***	-0.024***	-0.034***	-0.042***
	(0.002)	(0.004)	(0.006)	(0.009)	(0.010)
$Citation\text{-}Weighted\ Patents_t$	-0.009***	-0.012***	-0.013**	-0.012	-0.013
	(0.002)	(0.004)	(0.006)	(0.008)	(0.011)
$Patent\ Value_t$	0.019***	0.034***	0.043***	0.049***	0.054***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.017)
			Labor		
$Obsolescence_t$	-0.005***	-0.010***	-0.015**	-0.017**	-0.017*
	(0.002)	(0.004)	(0.006)	(0.008)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	-0.006**	-0.009*	-0.011	-0.011	-0.011
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$	0.013***	0.022***	0.028***	0.033***	0.036***
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
			TFP		
$Obsolescence_t$	-0.004	-0.008**	-0.011**	-0.015***	-0.014***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
$Citation\text{-}Weighted\ Patents_t$	0.000	0.008	0.009	0.006	0.014
	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)
$Patent\ Value_t$	0.017**	0.024*	0.029**	0.035***	0.039***
	(0.008)	(0.013)	(0.012)	(0.011)	(0.010)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity after adding measures of new innovation, the stock market-based patent value from Kogan et al. (2017) and citation-weight patent counts. The design follows that in Table 5.

Table A.3. Technology Obsolescence and Firm Distress and Failure

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
$Obsolescence_t$	0.0001	0.0006	0.0014	0.0018	0.0019
	(0.0003)	(0.0006)	(0.0010)	(0.0013)	(0.0015)

Notes. This table examines the relation between *Obsolescence* and firm bankruptcy (Chapter 11) using the same design as in Table 5 in the main text.

Table A.4. Heterogeneity Across Different Firm and Industry Characteristics, Controlling For Innovation Measures

Heterogeneity	Core Patents		Product/Process Patents		Competition	
	Core	Non-Core	Product	Process	High	Low
			Profits			
$Obsolescence_t$	-0.010*	-0.002	-0.014**	-0.004	-0.013**	-0.011
	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)	(0.014)
$Citation\text{-}Weighted\ Patents_t$	0.003	0.004	0.003	0.004	-0.000	0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
$Patent\ Value_t$	0.046***	0.046***	0.046***	0.046***	0.047***	0.055***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.012)
			Output			
$Obsolescence_t$	-0.015**	-0.002	-0.016**	-0.008	-0.020**	-0.004
	(0.007)	(0.007)	(0.008)	(0.005)	(0.009)	(0.012)
$Citation\text{-}Weighted\ Patents_t$	-0.016	-0.015	-0.016	-0.015	-0.024**	0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)
$Patent\ Value_t$	0.043***	0.043***	0.043***	0.043***	0.046***	0.046***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.011)
			Capital			
$Obsolescence_t$	-0.025***	-0.013**	-0.029***	-0.010*	-0.035***	-0.001
	(0.007)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$	-0.014**	-0.013**	-0.014**	-0.013**	-0.015**	-0.016
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)
$Patent\ Value_t$	0.042***	0.043***	0.043***	0.043***	0.044***	0.047***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

Heterogeneity	Core Patents		Product/Process Patents		Competition	
	Core	Non-Core	Product	Process	High	Low
			Labor			
$Obsolescence_t$	-0.010*	-0.006	-0.015**	-0.004	-0.018**	0.004
	(0.006)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$	-0.011	-0.011	-0.011	-0.011	-0.015**	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.014)
$Patent\ Value_t$	0.028***	0.028***	0.028***	0.028***	0.029***	0.031***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)
			TFP			
$Obsolescence_t$	-0.009**	-0.005	-0.010**	-0.006*	-0.012**	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
$Citation\text{-}Weighted\ Patents_t$	0.009	0.010	0.009	0.010	0.006	0.014
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)
$Patent\ Value_t$	0.029**	0.029**	0.029**	0.029**	0.032**	0.017***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.006)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity in different subsamples. This is the same design as in Table 7 in the main text, after adding new innovation measures SM and CW. The core vs. non-core (peripheral) patents are defined as the top technology class(es) that populate 50% of the firm's all patents. The product (disembodied) vs. process (embodied) innovation is defined using the textual description of patents based on Bena and Simintzi (2019). The product market competition is categorized into high vs. low based on the SIC3 HHI. The empirical design follows that in Table 5, only the $t + 3$ horizon is reported.

Table A.5. Robustness of *Obsolescence* Measure—Only General Patents In the Base

	High-Generality Patents			Low-Generality Patents		
	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
			Profits			
$Obsolescence_t$	-0.006***	-0.011*	-0.020**	-0.005**	-0.008	-0.007
	(0.002)	(0.006)	(0.009)	(0.002)	(0.005)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	0.002	0.003	0.024	0.002	0.004	0.024
	(0.005)	(0.012)	(0.017)	(0.005)	(0.012)	(0.017)
$Patent\ Value_t$	0.024***	0.046***	0.059***	0.024***	0.046***	0.059***
	(0.007)	(0.016)	(0.018)	(0.007)	(0.016)	(0.018)
			Output			
$Obsolescence_t$	-0.005*	-0.012	-0.019*	-0.006***	-0.011*	-0.007
	(0.002)	(0.007)	(0.011)	(0.002)	(0.006)	(0.011)
$Citation\text{-}Weighted\ Patents_t$	-0.005	-0.016	-0.007	-0.005	-0.015	-0.007
	(0.004)	(0.010)	(0.015)	(0.004)	(0.010)	(0.015)
$Patent\ Value_t$	0.020***	0.043***	0.055***	0.020***	0.043***	0.055***
	(0.007)	(0.016)	(0.020)	(0.007)	(0.016)	(0.020)
			Capital			
$Obsolescence_t$	-0.008***	-0.020***	-0.034***	-0.006***	-0.013**	-0.019**
	(0.002)	(0.007)	(0.011)	(0.002)	(0.005)	(0.008)
$Citation\text{-}Weighted\ Patents_t$	-0.009***	-0.013**	-0.013	-0.009***	-0.013**	-0.012
	(0.002)	(0.006)	(0.011)	(0.002)	(0.006)	(0.011)
$Patent\ Value_t$	0.019***	0.042***	0.053***	0.020***	0.043***	0.054***
	(0.004)	(0.012)	(0.017)	(0.004)	(0.012)	(0.017)

	High-Generality Patents			Low-Generality Patents		
	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
Labor						
$Obsolescence_t$	-0.005***	-0.011**	-0.015*	-0.004**	-0.011**	-0.007
	(0.002)	(0.006)	(0.008)	(0.002)	(0.005)	(0.008)
$Citation\text{-}Weighted\ Patents_t$	-0.006**	-0.011	-0.011	-0.006**	-0.011	-0.011
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.011)
$Patent\ Value_t$	0.013***	0.028***	0.036***	0.013***	0.028***	0.036***
	(0.003)	(0.010)	(0.014)	(0.003)	(0.009)	(0.014)
TFP						
$Obsolescence_t$	-0.008***	-0.010**	-0.013**	-0.005**	-0.007**	-0.001
	(0.003)	(0.004)	(0.006)	(0.002)	(0.004)	(0.005)
$Citation\text{-}Weighted\ Patents_t$	0.000	0.009	0.013	0.001	0.010	0.014
	(0.004)	(0.007)	(0.010)	(0.004)	(0.007)	(0.010)
$Patent\ Value_t$	0.017**	0.029**	0.039***	0.017**	0.029**	0.039***
	(0.008)	(0.012)	(0.010)	(0.008)	(0.012)	(0.010)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity in different subsamples. The core vs. non-core (peripheral) patents are defined as the top technology class(es) that populate 50% of the firm's all patents. The product (disembodied) vs. process (embodied) innovation is defined using the textual description of patents based on Bena and Simintzi (2019). The product market competition is categorized into high vs. low based on the SIC3 HHI. The empirical design follows that in Table 5, only the $t+3$ horizon is reported.

Table A.6. Robustness of *Obsolescence* Measure—Different Components of Technology Base

	Foreign-Country Patents			Non-Corporation Patents			Standard Essential Patents		
	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
Profits									
$Obsolescence_t$	-0.006**	-0.013**	-0.021**	-0.004*	-0.003	-0.004	-0.001	-0.016	-0.035**
	(0.002)	(0.006)	(0.008)	(0.002)	(0.006)	(0.008)	(0.005)	(0.010)	(0.014)
$Citation\text{-}Weighted\ Patents_t$	0.002	0.003	0.023	0.001	0.003	0.023	-0.011	-0.042**	-0.019
	(0.005)	(0.012)	(0.017)	(0.005)	(0.012)	(0.017)	(0.011)	(0.020)	(0.032)
$Patent\ Value_t$	0.024***	0.046***	0.059***	0.025***	0.048***	0.061***	0.035***	0.074***	0.106***
	(0.007)	(0.016)	(0.018)	(0.007)	(0.017)	(0.018)	(0.011)	(0.028)	(0.037)
Output									
$Obsolescence_t$	-0.006**	-0.012	-0.019*	-0.005**	-0.006	-0.005	-0.003	-0.015	-0.040***
	(0.003)	(0.007)	(0.010)	(0.002)	(0.006)	(0.008)	(0.004)	(0.010)	(0.016)
$Citation\text{-}Weighted\ Patents_t$	-0.005	-0.016	-0.008	-0.006	-0.017	-0.008	-0.011	-0.031*	-0.026
	(0.004)	(0.010)	(0.015)	(0.004)	(0.011)	(0.016)	(0.007)	(0.016)	(0.027)
$Patent\ Value_t$	0.020***	0.043***	0.055***	0.021***	0.046***	0.058***	0.032***	0.070**	0.096***
	(0.007)	(0.016)	(0.019)	(0.007)	(0.017)	(0.020)	(0.010)	(0.028)	(0.035)
Capital									
$Obsolescence_t$	-0.009***	-0.024***	-0.036***	-0.005***	-0.014***	-0.019**	-0.007*	-0.019**	-0.029*
	(0.002)	(0.006)	(0.010)	(0.002)	(0.005)	(0.008)	(0.004)	(0.009)	(0.015)
$Citation\text{-}Weighted\ Patents_t$	-0.009***	-0.014**	-0.014	-0.009***	-0.014**	-0.014	-0.011**	-0.027*	-0.031
	(0.002)	(0.006)	(0.011)	(0.002)	(0.006)	(0.011)	(0.005)	(0.016)	(0.025)
$Patent\ Value_t$	0.019***	0.043***	0.054***	0.020***	0.044***	0.056***	0.030***	0.071***	0.103***
	(0.004)	(0.012)	(0.017)	(0.004)	(0.012)	(0.017)	(0.008)	(0.023)	(0.030)

	Foreign-Country Patents			Non-Corporation Patents			Standard Essential Patents		
	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
					Labor				
$Obsolescence_t$	-0.004**	-0.011**	-0.011	-0.004***	-0.009*	-0.006	-0.001	-0.013*	-0.035***
	(0.002)	(0.005)	(0.008)	(0.001)	(0.004)	(0.007)	(0.003)	(0.007)	(0.012)
$Citation\text{-}Weighted\ Patents_t$	-0.006**	-0.011	-0.011	-0.006**	-0.011	-0.012	-0.018***	-0.047***	-0.072***
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.012)	(0.004)	(0.013)	(0.022)
$Patent\ Value_t$	0.013***	0.028***	0.036***	0.014***	0.029***	0.038***	0.024***	0.059***	0.085***
	(0.003)	(0.009)	(0.014)	(0.003)	(0.010)	(0.014)	(0.008)	(0.021)	(0.026)
					TFP				
$Obsolescence_t$	-0.007***	-0.013***	-0.015***	-0.003	-0.000	-0.002	-0.003	-0.013	-0.013
	(0.002)	(0.003)	(0.006)	(0.002)	(0.004)	(0.005)	(0.005)	(0.008)	(0.013)
$Citation\text{-}Weighted\ Patents_t$	0.000	0.009	0.013	0.000	0.009	0.014	-0.014*	0.009	0.019
	(0.004)	(0.007)	(0.010)	(0.004)	(0.007)	(0.010)	(0.007)	(0.015)	(0.032)
$Patent\ Value_t$	0.017**	0.029**	0.039***	0.018**	0.030**	0.040***	0.038***	0.060***	0.073***
	(0.008)	(0.012)	(0.010)	(0.008)	(0.012)	(0.011)	(0.009)	(0.017)	(0.023)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity in different subsamples. The core vs. non-core (peripheral) patents are defined as the top technology class(es) that populate 50% of the firm's all patents. The product (disembodied) vs. process (embodied) innovation is defined using the textual description of patents based on Bena and Simintzi (2019). The product market competition is categorized into high vs. low based on the SIC3 HHI. The empirical design follows that in Table 5, only the $t+3$ horizon is reported.

Table A.7. Robustness of Obsolescence Measure—Patents Owned

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.019***	-0.033***	-0.047***	-0.055***	-0.063***
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$	-0.001	-0.003	-0.003	0.001	0.015
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
$Patent\ Value_t$	0.022***	0.032***	0.041***	0.047***	0.053***
	(0.007)	(0.011)	(0.016)	(0.017)	(0.017)
			Output		
$Obsolescence_t$	-0.015***	-0.027***	-0.037***	-0.039***	-0.043***
	(0.002)	(0.005)	(0.006)	(0.008)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	-0.007*	-0.011	-0.020*	-0.018	-0.012
	(0.004)	(0.007)	(0.010)	(0.012)	(0.015)
$Patent\ Value_t$	0.019***	0.031**	0.039**	0.046**	0.051***
	(0.006)	(0.012)	(0.016)	(0.021)	(0.019)
			Capital		
$Obsolescence_t$	-0.021***	-0.038***	-0.051***	-0.058***	-0.065***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.009)
$Citation\text{-}Weighted\ Patents_t$	-0.011***	-0.016***	-0.019***	-0.018**	-0.020*
	(0.002)	(0.004)	(0.006)	(0.008)	(0.011)
$Patent\ Value_t$	0.017***	0.031***	0.038***	0.043***	0.048***
	(0.003)	(0.007)	(0.011)	(0.014)	(0.016)
			Labor		
$Obsolescence_t$	-0.011***	-0.020***	-0.026***	-0.031***	-0.037***
	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
$Citation\text{-}Weighted\ Patents_t$	-0.007***	-0.011**	-0.014*	-0.015	-0.015
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$	0.012***	0.021***	0.025***	0.030***	0.033**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.013)
			TFP		
$Obsolescence_t$	-0.005*	-0.011***	-0.013***	-0.009	-0.010
	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)
$Citation\text{-}Weighted\ Patents_t$	-0.000	0.007	0.008	0.006	0.013
	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)
$Patent\ Value_t$	0.016**	0.023*	0.028**	0.034***	0.038***
	(0.008)	(0.013)	(0.012)	(0.011)	(0.010)

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity after adding measures of new innovation, the stock market-based patent value from Kogan et al. (2017) and citation-weight patent counts. The design follows that in Table 5.

Table A.8. Summary Statistics for Asset Pricing Implications

Panel (a): For All Firms on CRSP

	count	mean	std	10%	25%	50%	75%	90%
$Size$	109079	1,589	6,260	9.000	29.000	131.000	659.000	2,775
$\log(BM)$	109014	0.716	0.713	0.151	0.288	0.521	0.897	1.445
$Ret(-1,0)$ (%)	100711	0.197	15.186	-16.398	-7.747	-0.171	6.667	16.667
$Ret(-12,-2)$ (%)	100412	11.088	58.410	-49.303	-24.591	2.616	33.138	74.661
Idiosyncratic Volatility	108637	0.041	0.029	0.015	0.022	0.033	0.051	0.077
SUE (%)	95466	-0.769	14.947	-4.010	-0.583	0.008	0.411	2.570
Patents/Assets (%)	109687	1.411	4.781	0.000	0.000	0.000	0.342	3.372
R&D/Market Equity (%)	109079	4.180	9.446	0.000	0.000	0.079	4.382	12.044
Innovation Originality	109741	5.332	8.241	0.000	0.000	0.000	9.000	15.917
Citations-Based Innovative Efficiency	109741	0.157	0.642	0.000	0.000	0.000	0.007	0.287
Patents-Based Innovative Efficiency	109741	0.087	0.331	0.000	0.000	0.000	0.000	0.192

Panel (b): For Firms with a Obsolescence measure

	count	mean	std	10%	25%	50%	75%	90%
$Obsolescence$	25577	0.216	0.361	-0.216	-0.005	0.208	0.427	0.661
$Size$	25536	5,478	17,829	38.000	132.000	595.000	2,647	10,948
$\log(BM)$	25533	0.600	0.514	0.160	0.282	0.475	0.766	1.152
$Ret(-1,0)$ (%)	25294	0.030	12.603	-13.689	-6.452	-0.395	5.745	13.525
$Ret(-12,-2)$ (%)	25280	13.501	49.220	-38.798	-15.430	8.133	33.259	65.589
Idiosyncratic Volatility	25393	0.029	0.019	0.012	0.016	0.024	0.036	0.052
SUE (%)	24924	-0.284	9.888	-1.776	-0.190	0.018	0.250	1.320
Patents/Assets (%)	25576	2.950	6.104	0.000	0.079	0.864	2.848	7.448
R&D/Market Equity (%)	25536	6.346	10.754	0.000	0.946	3.134	7.408	15.468
Innovation Originality	25577	11.356	9.007	2.000	6.000	9.635	14.222	21.500
Citations-Based Innovative Efficiency	25577	0.370	1.051	0.000	0.000	0.080	0.287	0.801
Patents-Based Innovative Efficiency	25577	0.205	0.462	0.000	0.000	0.071	0.203	0.478

Panel (c): For Firms with a Obsolescence measure, by Group

	Raw value				Percentile ranks		
	Low	Middle	High	All	Low	Middle	High
Number of firms	256	341	256	853			
Obsolescence	-0.120	0.251	0.607	0.247	15	50	85
Size	4,230	6,740	3,539	5,026	46	54	48
$\log(BM)$	0.583	0.605	0.678	0.620	46	50	54
$Ret(-1,0)$ (%)	0.481	0.139	-0.402	0.078	51	50	49
$Ret(-12,-2)$ (%)	13.188	14.865	13.100	13.829	49	51	49
Idiosyncratic Volatility	0.031	0.027	0.030	0.029	54	46	51
SUE (%)	-0.266	-0.272	-0.384	-0.304	49	50	51
Patents/Assets (%)	3.176	2.766	3.088	2.986	49	51	51
R&D/Market Equity (%)	5.845	6.240	6.626	6.237	49	51	50
Innovation Originality	11.419	10.787	10.236	10.812	51	52	47
Citations-Based Innovative Efficiency	0.461	0.363	0.347	0.387	49	51	50
Patents-Based Innovative Efficiency	0.220	0.221	0.232	0.224	47	51	51

Notes. This table summarizes firm characteristics used in the Section 4 at the firm-year level. Panel (a) provides the summary statistics for the entire universe of stocks on CRSP, and Panel (b) provides the summary statistics for those firms with a *Obsolescence* measure for the year. Panel (c) reports the time-series mean of cross-sectional average characteristics (both raw value and percentile ranks) of firms in each group. At the end of June of year t from 1986 to 2016, we sort firms with nonmissing obsolescencemeasure into three portfolios—–Low, Middle, High, based on the 30th and 70th percentile in *Obsolescence* in year $t-1$. Detailed variable definitions are provided in the Appendix.

Table A.9. Return Predictive Power of Technology Obsolescence—5 Sorted Portfolios

Panel (a): Value-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
1	0.949***	0.460***	0.471***	0.530***	0.462***	0.492***	0.495***	0.561***
	(0.268)	(0.099)	(0.100)	(0.104)	(0.110)	(0.109)	(0.109)	(0.108)
2	0.842***	0.318***	0.329***	0.289***	0.217**	0.333***	0.337***	0.319***
	(0.250)	(0.084)	(0.088)	(0.093)	(0.110)	(0.091)	(0.097)	(0.099)
3	0.649***	0.072	0.107	0.004	-0.125	0.032	0.059	0.020
	(0.250)	(0.085)	(0.089)	(0.089)	(0.091)	(0.089)	(0.094)	(0.090)
4	0.543**	-0.074	-0.023	-0.181*	-0.248***	-0.110	-0.055	-0.166*
	(0.242)	(0.082)	(0.092)	(0.094)	(0.095)	(0.085)	(0.100)	(0.093)
5	0.534**	-0.090	-0.012	-0.181	-0.204	-0.142	-0.062	-0.166
	(0.244)	(0.124)	(0.117)	(0.121)	(0.148)	(0.124)	(0.118)	(0.123)
1-5	0.415**	0.550***	0.484***	0.711***	0.666***	0.634***	0.557***	0.727***
	(0.179)	(0.159)	(0.151)	(0.160)	(0.186)	(0.162)	(0.156)	(0.158)

Panel (b): Equal-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
1	0.902***	0.228**	0.361***	0.398***	0.393***	0.200*	0.344***	0.395***
	(0.330)	(0.103)	(0.103)	(0.099)	(0.115)	(0.103)	(0.105)	(0.100)
2	0.946***	0.238**	0.369***	0.266***	0.198*	0.157*	0.290***	0.262***
	(0.319)	(0.096)	(0.092)	(0.086)	(0.113)	(0.090)	(0.090)	(0.088)
3	0.916***	0.190*	0.339***	0.228**	0.163	0.103	0.256***	0.221**
	(0.314)	(0.107)	(0.099)	(0.093)	(0.125)	(0.103)	(0.097)	(0.095)
4	0.804**	0.042	0.180*	0.101	0.027	-0.026	0.123	0.094
	(0.336)	(0.103)	(0.096)	(0.092)	(0.094)	(0.105)	(0.103)	(0.093)
5	0.754**	-0.048	0.147	0.093	0.052	-0.134	0.076	0.075
	(0.368)	(0.122)	(0.113)	(0.102)	(0.132)	(0.123)	(0.116)	(0.104)
1-5	0.148	0.276***	0.214**	0.305***	0.340***	0.335***	0.268***	0.320***
	(0.115)	(0.096)	(0.095)	(0.096)	(0.105)	(0.102)	(0.102)	(0.097)

Notes. This table presents monthly portfolio returns (in %) for portfolios sorted on *Obsolescence*. At the end of June of year t from 1986 to 2016, we sort firms based on their obsolescence measure into five portfolios—1–5 from low to high. All other analysis follow Table 10 in the main text.

Table A.10. Return Predictive Power of Technology Obsolescence

Panel (a): Value-Weight Portfolio

	Ind-adjret	Size/BM-adjret	Size/BM/Mom-adjret
Low	-0.181	0.159*	0.118*
	(0.172)	(0.083)	(0.068)
Middle	-0.314**	-0.060	-0.046
	(0.153)	(0.038)	(0.032)
High	-0.222*	-0.113	-0.114**
	(0.124)	(0.072)	(0.056)
Low-High	0.041	0.272*	0.231**
	(0.119)	(0.140)	(0.114)

Panel (b): Equal-Weight Portfolio

	Ind-adjret	Size/BM-adjret	Size/BM/Mom-adjret
Low	0.060	0.081*	0.072*
	(0.041)	(0.045)	(0.040)
Middle	0.008	0.032	0.031
	(0.035)	(0.028)	(0.024)
High	-0.071*	-0.123***	-0.113***
	(0.040)	(0.043)	(0.038)
Low-High	0.131**	0.204**	0.185***
	(0.066)	(0.080)	(0.071)

Notes. The portfolio industry-adjusted returns (Ind-adjret) are based on the difference between individual firms' returns and the returns of firms in the same industry (based on Fama-French 48 industry classifications). The portfolio characteristic-adjusted returns are computed by adjusting returns using 25 Size/BM portfolios (Size/BM-adjret, (Fama and French, 1993)), 125 size/BM/Mom-adjusted returns (Size/BM/Momentum-adjret, (Daniel et al., 1997)).

Table A.11. Return Predictive Power of Technology Obsolescence: Industry-Related Sorting

Panel (a): By-Industry Sorting: Value-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.834***	0.307***	0.329***	0.282***	0.178**	0.310***	0.326***	0.309***
	(0.247)	(0.063)	(0.061)	(0.061)	(0.073)	(0.071)	(0.069)	(0.068)
Middle	0.678***	0.108*	0.138**	0.064	-0.054	0.091	0.117*	0.083
	(0.238)	(0.063)	(0.065)	(0.061)	(0.070)	(0.066)	(0.070)	(0.064)
High	0.621***	0.043	0.068	-0.087	-0.084	0.008	0.028	-0.062
	(0.238)	(0.077)	(0.082)	(0.076)	(0.081)	(0.080)	(0.087)	(0.080)
Low-High	0.214**	0.264***	0.262***	0.368***	0.262***	0.302***	0.298***	0.370***
	(0.103)	(0.093)	(0.097)	(0.097)	(0.101)	(0.098)	(0.103)	(0.097)

Panel (b): By-Industry Sorting: Equal-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.918***	0.204**	0.347***	0.316***	0.285***	0.147*	0.300***	0.308***
	(0.326)	(0.092)	(0.091)	(0.087)	(0.110)	(0.089)	(0.091)	(0.087)
Middle	0.848***	0.110	0.256***	0.155*	0.070	0.025	0.176**	0.146*
	(0.319)	(0.096)	(0.086)	(0.079)	(0.100)	(0.091)	(0.085)	(0.081)
High	0.829**	0.079	0.238**	0.195**	0.167	0.015	0.185*	0.188*
	(0.350)	(0.110)	(0.105)	(0.096)	(0.120)	(0.110)	(0.108)	(0.098)
Low-High	0.089	0.124*	0.109	0.121*	0.118*	0.133**	0.115*	0.120*
	(0.067)	(0.064)	(0.066)	(0.065)	(0.064)	(0.066)	(0.068)	(0.064)

Panel (c): Industry-Demean Sorting: Value-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.852***	0.341***	0.341***	0.329***	0.245***	0.365***	0.358***	0.360***
	(0.253)	(0.067)	(0.066)	(0.069)	(0.078)	(0.075)	(0.073)	(0.074)
Middle	0.678***	0.103*	0.134**	0.040	-0.078	0.079	0.106*	0.058
	(0.235)	(0.058)	(0.059)	(0.057)	(0.070)	(0.062)	(0.064)	(0.060)
High	0.639***	0.058	0.103	-0.038	-0.044	0.024	0.065	-0.014
	(0.243)	(0.081)	(0.085)	(0.081)	(0.086)	(0.083)	(0.091)	(0.084)
Low-High	0.213*	0.283***	0.238**	0.368***	0.289**	0.341***	0.293***	0.374***
	(0.119)	(0.099)	(0.101)	(0.110)	(0.120)	(0.106)	(0.110)	(0.109)

Panel (d): Industry-Demean Sorting: Equal-Weight Portfolio

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.917***	0.203**	0.344***	0.317***	0.288***	0.150*	0.300***	0.310***
	(0.330)	(0.093)	(0.092)	(0.086)	(0.106)	(0.091)	(0.092)	(0.086)
Middle	0.849***	0.111	0.254***	0.145*	0.062	0.022	0.171**	0.135*
	(0.315)	(0.095)	(0.087)	(0.080)	(0.104)	(0.090)	(0.085)	(0.082)
High	0.831**	0.083	0.248**	0.213**	0.184	0.020	0.197*	0.207**
	(0.354)	(0.112)	(0.105)	(0.096)	(0.120)	(0.112)	(0.108)	(0.098)
Low-High	0.087	0.120*	0.096	0.104	0.104	0.130*	0.103	0.104
	(0.073)	(0.069)	(0.069)	(0.069)	(0.069)	(0.072)	(0.071)	(0.069)

Notes. This table presents monthly portfolio returns (in %) for value-weight and equal-weight portfolios sorted on *Obsolescence* within industry in panel (a) and panel (b), respectively; monthly portfolio returns (in %) for value-weight and equal-weight portfolios sorted on *Obsolescence* after demeaned by industry in panel (c) and panel (d), respectively. The definitions of the excess returns of one-month Treasury bill rate and a vast set of risk factors are the same as those in Table 10. Standard errors are reported in parenthesis.

Table A.12. Return Predictive Power of Technology Obsolescence: Value Weight Portfolios' Factor Loadings

Panel (a): Four-Factor + RMW + CMA Loadings

	MKT	SMB	HML	UMD	RMW	CMA
Low	0.958***	-0.048	-0.289***	0.011	-0.002	-0.119*
	(0.021)	(0.039)	(0.042)	(0.024)	(0.053)	(0.062)
Middle	1.009***	-0.099***	-0.195***	-0.073***	0.121***	0.231***
	(0.021)	(0.028)	(0.032)	(0.024)	(0.032)	(0.064)
High	1.018***	-0.001	-0.121***	-0.107***	0.151***	0.540***
	(0.024)	(0.045)	(0.041)	(0.029)	(0.050)	(0.066)
Low-High	-0.059*	-0.047	-0.167**	0.118***	-0.153**	-0.659***
	(0.033)	(0.060)	(0.067)	(0.044)	(0.061)	(0.102)

Panel (b): q-Factor Loadings

	MKT	SMB	Investment factor	ROE factor	Expected growth factor
Low	0.979***	-0.054	-0.468***	-0.069	0.254***
	(0.023)	(0.039)	(0.065)	(0.054)	(0.066)
Middle	1.026***	-0.113***	0.005	-0.032	0.244***
	(0.021)	(0.026)	(0.061)	(0.037)	(0.046)
High	1.013***	-0.036	0.405***	-0.031	0.104
	(0.024)	(0.049)	(0.072)	(0.048)	(0.074)
Low-High	-0.034	-0.018	-0.873***	-0.039	0.150
	(0.030)	(0.077)	(0.118)	(0.073)	(0.110)

Panel (c): Intangible Asset-Adjusted Four-Factor Loadings

	MKT	SMB	HML^{INT}	UMD
Low	0.997***	0.006	-0.287***	0.015
	(0.024)	(0.032)	(0.031)	(0.030)
Middle	0.979***	-0.116***	0.005	-0.045*
	(0.029)	(0.022)	(0.031)	(0.026)
High	0.935***	-0.053	0.197***	-0.068*
	(0.030)	(0.037)	(0.056)	(0.039)
Low-High	0.062	0.059	-0.484***	0.083
	(0.038)	(0.056)	(0.071)	(0.061)

Panel (d): Intangible Asset-Adjusted Four-Factor + RMW + CMA Loadings

	MKT	SMB	HML^{INT}	UMD	RMW	CMA
Low	0.968***	0.006	-0.189***	0.023	0.019	-0.234***
	(0.025)	(0.041)	(0.040)	(0.026)	(0.056)	(0.063)
Middle	1.010***	-0.068**	-0.092*	-0.060**	0.118***	0.125
	(0.022)	(0.031)	(0.052)	(0.028)	(0.037)	(0.081)
High	1.021***	0.021	-0.076	-0.101***	0.158***	0.489***
	(0.025)	(0.044)	(0.050)	(0.032)	(0.056)	(0.075)
Low-High	-0.053	-0.015	-0.113*	0.125***	-0.139**	-0.723***
	(0.034)	(0.060)	(0.068)	(0.047)	(0.070)	(0.109)

Notes. This table provides factor loadings of the value-weighted *Obsolescence*-sorted portfolio returns on the Fama-French Four Factors + RMW + CMA (robust-minus-weak, conservative-minus-aggressive) (Fama and French, 1992; Carhart, 1997), in panel (a); the factor loadings of the portfolio on the q-factors in Hou, Xue, and Zhang (2015), in panel (b); the factor loadings of the portfolio on the Fama-French Four Factors after replacing the value factor with the intangible-adjusted value factor (Eisfeldt, Kim, and Papanikolaou, 2020), in panel (c); and the factor loadings of the portfolio on the Fama-French Four Factors + RMW + CMA after replacing the value factor with the intangible-adjusted value factor (Eisfeldt, Kim, and Papanikolaou, 2020), in panel (d).