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TECHNOLOGICAL OBSOLESCENCE

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ABSTRACT

This paper proposes a new measure of technological obsolescence using detailed patent data. Using this measure, we present two sets of results. First, firms' technological obsolescence foreshadows substantially lower growth, productivity, and reallocation of capital. This finding applies mainly for obsolescence of core innovation and embodied innovation, and it is stronger in competitive product markets. Second, in stock markets, high-obsolescence firms under-perform low-obsolescence firms by 7 percent annually. Using analyst forecast data, we show this is due to a systematic overestimation of future profits of obsolescent firms. The measure contains incremental information about firm innovation relative to measures focusing on new innovation.

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The Schumpeterian narrative of creative destruction has two pillars: creation and destruction. The well-studied one is the innovation process—creative innovation is produced and adopted, leading to the expansion of product variety, the increase of productivity, and eventually the growth of the economy. Empirical explorations along this line take advantage of our ability to capture the arrival of new and novel innovation, most noticeably using widely accepted patent-based measures.[1]

This paper focuses on the destruction pillar, which has attracted less attention. As innovation creates winners and economic gains, it also creates losers and renders value losses of existing technologies. This destruction mechanism functions through *technological obsolescence*: existing technologies, which once were at the frontier, become less valuable when technologies evolve. Prominent examples of obsolete technologies include the steam engine, fax machines, floppy disks, photographic film, and many others. Technological obsolescence is conceptually important. In endogenous growth theories, technological obsolescence negatively impact the profitability and productivity of firms owning or operating such technologies and triggers capital reallocation.[2] Moreover, financial markets react to technological evolution, which in turn may affect the cost of financing innovation and long-term innovativeness of the economy.[3]

Despite its importance, technological obsolescence is rarely studied empirically, because of the scarcity of directly observable measures. An ideal measure should capture the level of technological obsolescence that each firm experiences in its existing technology stock at each point in time. The measure should also reflect the combined technological disruption from various sources: industry competitors' research and development (R&D), the emergence of new markets and industries, or sometimes cannibalization by a firm's own successful innovation through variety expansion or quality upgrade. This paper constructs such a measure of technological obsolescence, and studies its relationship to subsequent firm performance and financial market returns.

We first proposes the measure, *Technological Obsolescence*, for each firm in a given year. This

[1] Recent work combines patent information with stock market data upon patent approval (Kogan, Papanikolaou, Seru, and Stoffman, 2017, *hereafter* KPSS) or text-based method (Bellstam, Bhagat, and Cookson, 2020; Kelly, Papanikolaou, Seru, and Taddy, 2021; Bowen, Frésard, and Hoberg, 2021) and achieves remarkable success in connecting the arrival of innovation with firm growth, active resource reallocation, and economic prosperity.

[2] See, for example, Grossman and Helpman (1991), Aghion and Howitt (1992), Klette and Kortum (2004), Lentz and Mortensen (2008), Aghion, Akcigit, and Howitt (2014), Acemoglu et al. (2018), Akcigit and Kerr (2018), Garcia-Macia, Hsieh, and Klenow (2019), and Hoberg and Maksimovic (2021).

[3] Kogan and Papanikolaou (2019) provide a recent survey of the literature that introduces technological innovation into asset pricing.

is a measure about the stock of a firm's existing technologies. A firm's technologies become more obsolete if they become less valuable in generating new innovation and less desirable in the market. The measure construction takes three steps to capture this intuition. First, we define a firm's technology base as all the patents that it ever cited in its own innovation up to that year. It proxies a firm's exposure to various technologies. 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 over time and that this process can be captured using the *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 define technological obsolescence as the rate of change in citations made to each firm's technology base over a certain time window. This is in the same spirit as a share-shift style measure that combines firms' technology exposures and external technology evolution.

Consider the following example for illustration. Imagine that a firm owned 20 patents in its patent portfolio in the 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 the frontier. Intuitively, this captures the obsolescence of a firm's technology base due to heterogeneous exposures to various innovation paths. To ensure that this measure is less affected by a firm's own characteristics, we exclude the focal firm's own innovation from the technology base and its own self-citation when calculating the citation dynamics.

Two cases studies help validate the measure. In the first sector-specific study, we focus on the Hard Disk Drive (HDD) industry. Taking advantage of prior research that defines the emergence of new technologies and the obsolescence of old ones (Christensen, 1997; Igami, 2017), we show that our measure captures this evolutionary process closely—patents associated with the old HDD generation have higher obsolescence when the new generation emerges. In the second study, we document that arrivals of radical innovation, as defined in Kelly et al. (2021), are followed by technological obsolescence of disrupted firms and industries.

Based on this measure, a firm's technology portfolio experiences on average 4–7 percent obsolescence annually. This average obsolescence rate is consistent with the knowledge capital depreciation used in the literature (see De Rassenfosse and Jaffe (2017) for a recent example). Importantly, there are losers and winners from the technology evolution, with the winning 25 percent of firms enjoying negative or minimal obsolescence and the bottom 25 percent of firms' technology being disrupted by 7–16 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 is within-industry-year. These empirical features allow our analysis to control timing-varying industry trends, which closely resonates theories that often model a single industry.

The measure has a few desirable properties. To begin, it captures various sources of technology disruption—within-firm innovation that cannibalizes a firm's own technology, industry competitors' technological breakthroughs, or disruptive innovation from outside the industry. In fact, we show that these three sources are all important in explaining variations in technological obsolescence. Second, the methodology can be flexibly extended to isolate obsolescence originating from different types of firm innovation. The measure can be tailored to capture the obsolescence of core vs. peripheral patents, embodied and disembodied patents, or 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). Lastly, it primarily builds on 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.

We build *Technological Obsolescence* for public US firms that filed patents from 1986 to 2016. We perform two sets of tests to explore the relation between technological obsolescence and (i) firm growth and capital reallocation, and (ii) asset prices and cost of financing innovation.

Firm Growth and Productivity. First, we examine the relation between technological 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. We provide a direct test for this theoretical prediction.

Firms experiencing larger obsolescence with their technologies have significantly lower growth. Over a five year period, compared to firms in the same industry-year, one standard deviation higher in obsolescence is associated with slower growth in profit (3.1 percentage points), output (3.2 percentage points), capital (5.2 percentage points), and employment (1.9 percentage points). The same increase in obsolescence is associated with a 1.4 percentage point decrease in 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. To our knowledge, this is the first empirical evidence that connects a direct technological obsolescence measure with firms.

Technological obsolescence provides complementary information that is largely independent of measures of new innovation. When we simultaneously include them in the analysis, the economic impact of technological obsolescence remains virtually the same and statistically robust. Stock market-based patent value, as a measure for new innovation, strongly relates to growth and allocation, and citation-weighted patent counts are fragile when testing the implications for firm growth, consistent with KPSS. In other words, technological obsolescence is not simply failing to innovate. Indeed, in classic endogenous growth models like Klette and Kortum (2004), the destruction process is often modeled as an independent process from a firm's innovation arrival process. We also compare *Technological Obsolescence* with those measures of technology disruption that use valuable patents by public industry competitors (i.e., "other firms' win is my loss").[4] When being introduced into the same empirical model, the obsolescence measure remains economically sizable and statistically significant. Therefore, our measure successfully captures disruptive innovations that could happen outside the industry domain, such as those by firms in other industries, in research institutions and foreign corporations, or even the firm's own innovation.

The relation between technological obsolescence and firm outcomes varies across innovation types and product market conditions. 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 (e.g., engine technology in an automaker) and milder or negligible when it occurs in peripheral areas (e.g., the entertainment system of the same automaker). Furthermore, we test the idea that embodied innovation, such as those new products that will require an adjustment of physical and human capital (Berndt, 1990),

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

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.

Stock Returns and Earnings Expectations. How do financial markets incorporate information about technological obsolescence? We find that firms that have high realized technological obsolescence earn lower future returns than firms that have lower technological obsolescence. In a sorted-portfolio exercise, the average portfolio return monotonically decreases with technological obsolescence. A spread portfolio that buys low-*Obsolescence* firms and shorts high-*Obsolescence* firms earns a value-weighted excess return of more than 7 percent annually. This spread portfolio has an alpha of 57 basis points ($t = 3.931$) monthly, or 7.1 percent per year, in a model with Fama and French (2015) five-factor and momentum. 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).

This abnormal return pattern means that the price of high-*Obsolescence* firms are too high today, thus the lower future returns. We show that this can be explained by investors failing to fully incorporate technological movements into expectation formation about innovative firms in deterioration. We investigate this explanation using observed earnings per share (EPS) forecasts by financial analysts from I/B/E/S, following Bouchaud et al. (2019). We find that analysts' forecasts on future earning are overly optimistic for the deteriorating firms relative to the non-deteriorating firms. After all, technological obsolescence is a slow-moving and complex process. If investors, as shown by the extensive psychology literature, pay less attention to and weigh less on this complex information, we would expect that markets misprice the obsolescence of technologies (Hirshleifer, Hsu, and Li, 2018; Cohen, Diether, and Malloy, 2013; Bouchaud et al., 2019; Enke and Graeber, 2019).

Related Literature. The ability to track innovation capital is a central question in the literature bringing intangible capital into economic models. More effort has been devoted to the arrival of new innovation. However, the depreciation and destruction of innovation capital is equally important for macro (Griliches, 1998; Corrado, Hulten, and Sichel, 2009; Crouzet and Eberly, 2020) and financial economics (Peters and Taylor, 2017; Eisfeldt, Kim, and Papanikolaou, 2020; Biasi and Ma, 2021). The traditional approach estimates 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 approaches such as patent renewal (Pakes and Schankerman, 1984). The key novelty of this measure is to capture technological obsolescence at the fine unit of firm-year level, presenting significant heterogeneity in the cross-section. The measure further allows for direct tests of creative destruction leveraging firm-level settings to investigate operational performance and stock returns.

This paper complements work that investigates 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). The leading approach relies on calibration or estimation of structural models using reallocation data (Davis, Haltiwanger, and Schuh (1996) are the pioneers in this effort). In contrast, our approach builds a direct measure using detailed patent data and tests theoretical predictions. BSV and KPSS construct intuitive patent-based measures of the potential business-stealing effects of competitors' innovation. Our measure of technological obsolescence does not make assumptions about product market competition and innovation spillovers. Moreover, this measure captures various sources of obsolescence and disruption, and it provides additional information compared to these competitors' innovation measures.

This paper also joins a growing literature that explores the life cycles of knowledge, products, and industries, and their roles in helping us understand finance and investment behaviors (Maksimovic and Phillips, 2008; Hoberg and Maksimovic, 2021; Bustamante, Cujean, and Frésard, 2020). This research shows that identifying the stage in a firm's life cycle can help clarify conflicting evidence about corporate investment and performance, and the novelty often comes from the "decline" stage (Hoberg and Maksimovic, 2021). This paper contributes to this effort by continuously tracking the technological cycle a firms goes through. We also provide the first evidence on financial market performance in response to this evolutionary process.

1. Technological Obsolescence: Data and Measurement

This section starts by describing data collection. We then discuss the construction process of the key measure of *Technological 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

We obtain patent data from the United States Patent and Trademark Office (USPTO).[5] 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 on the patent's application and grant year. This database is linked to Compustat using the bridge file provided by NBER (up to the year 2006) and KPSS's data repository.[6] For later years, 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). The main analysis focuses on US public firms between 1986 and 2016. As discussed below, this window allows us to partially mitigate the truncation problems in the patent data. These problems occur because researchers do not observe full patent information for patents granted before 1976 and for patent applications that had not yet been granted by the time of sample construction (Lerner and Seru, 2021).

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 the year 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 p—we call these backward citations made by p. On average, each patent makes fifteen backward citations. For the latter, we observe all cases when p is cited by a successfully granted patent and the timing of those citations. These are forward citations received by p.[7]

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

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

[7]The forward citation process has a well known right-truncation problem (Hall, Jaffe, and Trajtenberg, 2001),

1.2. Constructing Technological Obsolescence

We construct a firm(f)-year(t)-level variable, termed as *Technological Obsolescence*$^{\omega}_{f,t}$ (*Obsolescence* for short), to capture the ω-year (between $t-\omega$ and t) rate of obsolescence experienced by firm f. The method builds on the literature of bibliometrics and scientometrics that measures the obsolescence and aging of a scientific discipline. 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 researcher's 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, not necessarily owned by the firm itself, but 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, roughly ten percent per year.[8] 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).

Second, despite the within-firm stability of the technology base, there are sizable cross-firm variations of technology bases within the same industry. This leads to the possibility of capturing within-industry-year variations of the exposures to the technology evolution. For any two firms in the same SIC3 industry, we can calculate the pair-wise overlap ratio of firms' technology base, which is defined as the number of patents in the base intersection over the number of patents in the

because patents, particularly recently approved ones, could receive many citations in the unobserved future. We will discuss this issue in the context of the analysis.

[8] 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 only mild growth.

union of the two bases. More than 90% of the pairs have an overlap ratio of zero. Even when 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 with subscript indicating the year the citation is calculated.

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 frontier of innovation production and commercialization. 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).

Even though 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 patterns of citation dynamics of patents. We show time-series variations within each patent, i.e., patents go from unknown, to being widely cited, to cooling down; and we also show cross-sectional variations across patents and technology fields of such citation dynamics. These give us the source of variations for 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 value of $Obsolescence$ means a greater decline in the value and utility of a firm's knowledge within the ω-year period, i.e., fewer new patents build on the firm's technology base. This is a within-firm growth measure. It naturally differences out effects of firm size and the size of knowledge space, and it mitigates systematic differences of citation norms across different sectors.

A few caveats remain as to the proper way to interpret the measure. First, we implicitly make the assumption that an increase in citations is a sign of increased value and usefulness of technology in innovation production. Although there may be outlier industries or firms—for example, one could imagine that a decrease in citations might be a sign of consolidated market power—it is widely accepted since Caballero and Jaffe (1993) that higher citations reflect higher value. This is further confirmed by Kogan et al. (2017) who connect citations to commercial value. Second, it is worth noting that an increase in citations received by any given patent is a combination of both scientific popularity and commercial viability. There may be cases when breakthrough innovation becomes widely adopted only a few years after being created—our measure is capable of capturing this whole dynamic.

The measure is also flexible when accommodating different variations. *Obsolescence* can be constructed for different types of patents owned by a firm—core vs. peripheral (Akcigit, Celik, and Greenwood, 2016) or 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 the more general purpose technologies or standard essential patents. In Section 2.5, these different versions of the measure will be used to further isolate variations to technological obsolescence independent of firm operations.

1.2.1. Alternative Construction. The economic logic behind the above measure construction is to track citation movements around a firm's technology stock. Our main construction relies on non-self citations made to the technology base of a firm after excluding a firm's own patents from this base. A natural alternative candidate to measure obsolescence is the changes of annual citations made to f's *own* patents, instead of those to the technology base. 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.

The difference between the two approaches is the extent to which the base is exposed to a firm's own idiosyncratic shocks that are not innovation relevant, or the extent to which it is reversely affected by firms' own performance. In the Appendix, we show that this alternative measure, not surprisingly, yields even stronger results in all our analyses.[9] However, this measure is more exposed

[9] The correlation between this alternative measure and the primary technological obsolescence measure is 0.361.

to alternative interpretations that will complicate 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, or product market performance. Our construction—by using the base excluding f's own patents and tracking only citations not made by f—is closer to capturing the obsolescence driven by movements of technology fields themselves.

1.3. Case Studies

1.3.1. The HDD Industry, 1985 to 1995. Before entering the analysis stage, we provide a case study to illustrate how our technological 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.[10] This industry has been an innovation economist's favorite for a few decades (Christensen, 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 remains 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 that when 3.5-inch technology started to emerge in the industry, those technologies that supported the 5.25-inch HDD would become obsolete, i.e., the obsolescence measure increases. Instead of showing this using firm-level obsolescence, we show this using patents for transparent comparison.

[Insert Figure 1 Here.]

We show two pairs of patents, corresponding to two different types of core technologies associated with building HDDs.[11] The first pair of patents are general-design patents of HDD. For

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

[11] For readers interested in learning more about HDD patents, we hereby describe the procedure used in building the patent sets for the case study. To identify HDD-related patents, we follow Igami and Subrahmanyam (2019) and focus our main example search among patents that are coded as NBER patent category "360 - Dynamic Magnetic Information

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 1, panels (a) and (b), we find that the obsolescence scores of those two patents differ significantly and the trends diverge at the end of the 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 larger than its 3.5-inch counterpart during the transition.

1.3.2. Technological Obsolescence after Breakthrough Innovation. We present another piece of validating evidence that allows us to go beyond just one industry. Specifically, we explore the technological obsolescence of a firm around the arrival of breakthrough innovation in technology fields related to its own innovation activities. If our technological obsolescence works well, we expect to see an increase of *Obsolescnece* in affected firms after those breakthrough innovations.

[Insert Figure 2 Here.]

To do so, we take advantage of the the breakthrough innovation identified in Kelly et al. (2021). We define breakthrough innovations as those in the top 0.5% in their novelty measure. We consider a firm to be affected by those breakthrough innovations if it innovates in the technology class of the breakthrough patents. Figure 2 presents a simple difference-in-differences figure. It shows that for firms in which the technology fields welcome a breakthrough innovation, the average *Obsolescence* jumps. This again validates the measure's ability to pick up technological evolution.

1.4. Descriptive Statistics of *Technological Obsolescence*

Table 1 shows summary statistics for technological 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

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.

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 percent 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 receives 24 percent fewer follow up citations. For $\omega = 5$, the mean of 19.39 means that the five-year obsolescence scores 19.39 percent on average, roughly 3.9 percent per year over the five-year window.

[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 are standard in the literature, and we refer interested readers to KPSS for details.

The arrival of new innovations is 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 lives, 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.

1.4.1. Decomposition of *Technological Obsolescence*. *Obsolescence* can vary across industries (defined at the SIC3 level), 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. Technological 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 but across firms, scoring 60 percent. Across industry-year, but within the same industry, the variation is 30 percent of the total. These two patterns tell us that industry-year trend is important for capturing technology evolution and that during the same trend, there are winners and losers, creating large heterogeneity across firms.

1.4.2. Sources of Technological Obsolescence. As summarized in Garcia-Macia, Hsieh, and Klenow (2019), a firm's technological obsolescence could originate from cannibalization by the firm's own new innovation (Christensen, 1997; Igami, 2017), by the new technological breakthroughs of a firm's industry rivals (BSV, KPSS), or from innovation from outside the boundary of the specific industry (e.g., AirBnB disrupting hotels; iPad and Kindle disrupting traditional printing copies).

[Insert Table 3 Here.]

Table 3 presents a simple analysis that projects *Technological Obsolescence* on three dimensions new innovation measures that correspond to the three disruptive sources above. That is, 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 technological obsolescence is associated with all three potential sources of technology disruption, and they seem to share similar magnitudes in terms of affecting technological 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).

2. Technological Obsolescence and Firm Growth

In a vast set of models, firms' existing innovation portfolios are destructed at a certain rate, leading to technological obsolescence; realized technological obsolescence is followed by lower output and profits of the firm and also by reallocation of capital and labor away from the firm (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 this section, we provide, to our knowledge, one of the first direct tests of this relation. We also jointly analyze technological obsolescence with the arrival of new innovation, and with the alternative measures of technology disruptions based on competitors' new inventions (i.e., "competitors' win is my loss"). We discuss the insights generated from those comparisons and the value of our measure.

2.1. Method

Our analysis in this section takes the form of equation (2), which follows KPSS closely,

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

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 (constructed based on the methodology of Olley and Pakes (1996) using the estimation procedure in İmrohoroğlu and Tüzel (2014), denoted as TFP).

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.[12] In other words, the timing in the analysis is: taking $t = 2000$, we use the technological 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 measures 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 grow more slowly and may also be more exposed to obsolescence in their patent portfolios. We also control for firm idiosyncratic volatility and firm age. All measures are winsorized at the 1% and 99% levels. 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 analyses, 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 we 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 lower output of 3.1 and 3.2 percentage points, respectively, over a five-year horizon. We also observe a gradual reallocation of resources away from the obsolete firm. Capital stock decreases by 5.2 percent during the same five year period, and total employment decreases by 1.9 percent.

[12] Results with other ω parameter values are presented in Appendix Table A.1 and Table A.2.

We find that a one standard deviation higher in technological obsolescence is associated with a 1.4 percentage point lower in productivity measured using TFP over five years.

[Insert Table 5 Here.]

Next, we compare the technological obsolescence measure with the new innovation measures. The analysis follows the same structure as in equation (2), but adds 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 make three observations. First, technological obsolescence captures additional and largely complementary 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 little change in both economic magnitudes and statistical significance. This suggests the *Obsolescence* measure achieves the goal of capturing the fading of a firm's existing technology, which can be quite empirically separated from the contemporary arrival of new innovation. Or in other words, technological obsolescence is not simply "not innovating."

Second, as a purely patent-based measure, technological obsolescence outperforms the well-established 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.

Lastly, 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. The impact of technological 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.[13]

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

Why is technological 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 technological obsolescence position should have at most a mild effect 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 markets 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 updating is not frictionless. 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

In Table 7 we present several key heterogeneity analyses.[14] 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 (e.g., an engine-related patent for an automaker) are higher for a firm than those of peripheral patents (e.g., 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

[14] Appendix Table A.4 presents heterogeneity analysis with alternative control variables.

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.

[Insert Table 7 Here.]

We then introduce those two versions of the *Obsolescence* measure into our main model in equation (2). Due to limited space, we only show $\tau = 3$, the three-year time horizon, for the dependent variable. Obsolescence of a firm's core patents drives most of the findings. In profit and output analysis, the effect of technological 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 rest 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 is complementary to existing investments; in contrast, product (embodied) innovation is 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 more quickly in competitive industries. For instance, in a high-HHI industry, one standard deviation higher in technological obsolescence is associated with a 3.9 percent decrease of capital stock and a 2.0 percent decrease of total employment within the three year horizon. These effects are virtually zero for industries where competition is less fierce. The implication is that 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 the 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 values of firms in the same SIC3 category. BSV also aggregates innovation activities measured using R&D input by competitors.

These measures have strong economic intuitions. In a wide range of innovation models, "competitors' win is my loss." These measures 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 relies on several 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 for within-firm cannibalization. (ii) It relies on assumptions about one's industry peer group and of the homogeneous relevance of industry competitors. This assumption can be very strong given what we document above in Figure A.6 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, 2021). (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). Technological 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 provides additional information compared to the earlier leave-me-out style measures.[15] Moreover, in most of the analysis,

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

technological obsolescence seems to more robustly explain firm profitability and growth patterns, compared to SM of competitors. The coefficients associated with Competitors' SM are consistently 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.

2.5. Strengthening *Obsolescence*-Driven Interpretations

As in KPSS, our firm-level tests do not establish a causal relationship between technological 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 or 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" technological obsolescence to fall.

Two parts of the analysis so far already guard against these concerns. 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 citations 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 elevates the bar for any alternative interpretation that may function without technological obsolescence. For instance, an alternative interpretation would need to explain why, without going through the technology channel, 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 efforts, we would like to further strengthen the technological obsolescence-driven interpretation. In the Appendix, we provide several additional variations of the *Obsolescence* variable. The central motivating principle in those additional analyses is that 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 that are less contaminated by a firm's own recent past operations and performance. 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 other 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. Technological Obsolescence and Stock Returns

How do financial markets react to technological obsolescence? This is an important question for asset pricing that concerns the implications of technology factors, and it is also an important question for those concerned with the cost of financing innovation and resource allocation. In this section, we explore this question in two steps. We first investigate return patterns around technological obsolescence, and then we discuss the economic mechanism and potential implications.

3.1. Technological Obsolescence and Cross-Sectional Stock Returns

We start by examining average returns on portfolios formed using *Obsolescence*. 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).

The sorting procedure goes as follows. 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 technological obsolescence, the measure is publicly observable at the end of year $t-1$ and does not incorporate any forward-looking information. These portfolios are held over the next twelve months, from July of year t to June of year $t+1$. We compute value-weighted monthly returns and equal-weighted monthly returns for those portfolios. No additional filters are used in selecting the sample, although the results are robust to additional filters like the price filter (e.g., lagged share prices above five dollars).

[Insert Table 9 Here.]

In Table 9 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 takes 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.9 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), and 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. Specifically, 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). Lastly, 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 9. 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 alpha. 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.10. 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.11. The effect is also robust when we perform the portfolio sorting using by-industry breakpoints each year or using the industry-year-demeaned *Obsolescence* measure, shown in Table A.12. In Appendix Table A.13, we examine the ability of technological obsolescence to predict the cross section of stock returns using monthly Fama-MacBeth regressions (Fama and French, 1992) and find consistent results with the portfolio sorting results.

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.14.

3.2. Obsolescence, Earnings Expectations, and Mispricing

So far, the results show that obsolete firms have lower future stock returns, and this is true after adjusting commonly used risk factors and firm-level characteristics. Why? We discuss two streams of explanations. We first discuss the mispricing-based explanations, which includes belief-based rationale and those based on non-traditional investor preferences. We then discuss potential connections to risk-based explanations.

Our primary hypothesis centers around incorrect beliefs formed around technological obsolescence that could lead to mispricing. Prior studies show that financial markets can be quite responsive to the arrival of new innovation (Pakes, 1985; Austin, 1993; Hall, Jaffe, and Trajtenberg, 2005; Nicholas, 2008). However, technological obsolescence is a more complex, slow-moving, and less attention-grabbing process. These features may not be fully incorporated by investors and thus may lead to mispricing. For example, technological obsolescence would predict poorer stock returns in the future if investors cannot fully absorb the poor future performance of the high-*Obsolescence* portfolio (i.e., under-reaction to technological obsolescence).[16]

We test whether investors form incorrect expectations about future profitability of firms with

[16]Indeed, earlier research shows that investors face difficulties in assessing nuanced features in even new innovative assets (Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2018).

different technological obsolescence. To do so, we examine a setting of analysts' forecasting errors using I/B/E/S data. I/B/E/S provides data on earnings per share (EPS) forecasts by financial analysts since the 1980s. Analysts are professional forecasters whose forecasts are not cheap talk, and this is a desirable feature for researchers. This setting has been used to explore incorrect beliefs of investors (Bordalo et al., 2019; Bouchaud et al., 2019; Bordalo et al., 2020).

Our data construction process follows Bouchaud et al. (2019) closely. We obtain analyst-by-analyst EPS forecasts from the I/B/E/S Detail History File (unadjusted). We keep all forecasts that were issued within three months after an announcement of total fiscal year earnings. We focus on analyst EPS forecasts for the current fiscal year and on forecasts for one and two fiscal years ahead. Only the first forecast is kept if multiple forecasts were issued by the analyst for the same firm and the same fiscal year during this 90-day period. We use these detailed analyst-by-analyst forecasts to calculate the firm-level consensus EPS forecast. Specifically, to compute the forecasts for one- and two-year-ahead earnings issued in year t, denoted as $F_t\pi_{t+\tau}$ (with $\tau = 1,2$), we calculate the median of all forecasts submitted during the three-month time window defined above. Next, we match actual reported EPS from the I/B/E/S unadjusted actuals file with the calculated consensus forecasts. The stock split event, which could affect the data accuracy, is adjusted following Bouchaud et al. (2019) and the papers cited therein. The final sample includes all firm-level observations with fiscal years ending between 1986 and 2016. This firm-year panel of forecast (errors) is connected to the firm-year panel used in previous sections.

The model regresses forecast errors on *Obsolescence* in equation (3),

$$\frac{\pi_{f,t+\tau} - F_t\pi_{f,t+\tau}}{P_{f,t-1}} = a + b_{t+\tau}Obsolescence_{t-1} + \varepsilon_{t+\tau}, \tag{3}$$

for $\tau \in \{1,2\}$. The term $\pi_{f,t+\tau}$ denotes the firm's realized EPS. The term $F_t\pi_{f,t+\tau}$ denotes the consensus EPS forecast. The forecasting error $(\pi_{f,t+\tau} - F_t\pi_{f,t+\tau})$ is normalized using the stock price at the fiscal year-end of the previous year, that is, $P_{f,t-1}$. We allow error terms to be correlated over time and within firm.

If expectations were formed rationally and technological obsolescence was fully incorporated in expectation formation, expectation errors $(\pi_{f,t+\tau} - F_t\pi_{f,t+\tau})/P_{f,t-1}$ should have zero mean conditional on the information available at t. If $b \neq 0$, this would suggest that forecasters do not incorporate the available information on technological obsolescence in a fully rational way. In the estimation, we allow for a nonzero constant a, which captures the fact that expectations may have a constant positive bias as found in prior literature.

[Insert Table 10 Here.]

Results from estimating equation (3) are reported in Table 10. We find that the forecast error is systematically negatively related to *Obsolescence*, i.e., $b < 0$. This finding is consistent with the idea that analyst expectations are non-rational and that analysts tend to "under-react" to technological obsolescence. In other words, they do not fully expect how poor the future performance can be in obsolete firms.

Thus far, we have given a belief-based explanation for the low returns of high-*Obsolescence* stocks. We have also examined whether these low returns can be explained by non-traditional investor preferences, such as those captured by prospect theory. Specifically, we take a recent model by Barberis, Jin, and Wang (2021) that makes quantitative predictions about stock returns when investors have prospect theory preferences and check whether it can explain our results. In this model, a stock earns a low average return when it is highly skewed or has a low capital gain overhang, so that the average investor's holding of the stock is trading at a loss relative to purchase price. The model is qualitatively consistent with our results: high-Obsolescence stocks are indeed highly skewed and have low gain overhang. However, we find that, quantitatively, the model can only explain 5-10% of the alpha spread between high- and low-*Obsolescence* stocks.[17]

Overall, financial markets seem to have difficulties in fully incorporating technological obsolescence in asset prices, and the under-reaction favors the obsolete firms. To the extent that the mispricing may impact the cost of capital and capital budgeting (Stein, 1996; Baker, Stein, and Wurgler, 2003), especially given the fact that innovative firms are often more equity-dependent, this may have long-term consequences on innovation productivity of the economy.

3.3. Obsolescence Risk and Stock Returns

In this brief section, we connect the return patterns to the asset pricing literature modeling technological changes as an important source of economic risks priced on the market (Kogan and

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

Papanikolaou, 2019). A commonly shared idea in these 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.

Our measure of technological obsolescence is not the most ideal to directly test those models since it is about *realized* obsolescence rather than about future risks. Having this background in mind, we explore the possibility of using our measure to capture future obsolescence risks and provide support to the technology risk-based asset pricing predictions. The key insight from our analysis is that firms that experience *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 has 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 a lower (higher) risk premium in the future.

[Insert Figure 3 Here.]

Figure 3 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 do we expect the low-$Obsolescence$ portfolio to experience an increase in technological obsolescence but an increase in the conditional volatility of technological obsolescence in the future as well. In panel (b), we show that the jump of obsolescence volatility is higher for the portfolio of firms that currently have low obsolescence.

4. Concluding Remarks and Future Directions

In this concluding remark, we would like to share what we think are some limitations of the current work and our suggestions for future research.

One promising future direction for future research is to track down the origin of technological obsolescence, i.e., the chain of technology replacement. 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 so on. The goal seems very straightforward, but the execution faces a lot of challenges for a large scale when different fields are involved. Our case study on the HDD industry can be viewed as a single-sector example of this relation. Some possible methods that may help achieve this goal include citation network, keywords, patent categorization coding, and textual analysis.

Another interesting question that future work can make progress on is to examine how firms actively react to technological obsolescence and regain their innovation edge. Potential connections to the literature on patent racing, the organization of innovation, and the theories of the firm could potentially generate some interesting insights in this topic. The question would be more interesting after taking into account the fact, as documented in the paper, that investors do not fully incorporate technology into allocating resources.

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 interconnection between technology evolution and stock prices—both at the aggregate level and at the cross-section. The route that is particularly interesting to us is to adapt the measure's logic to create a risk measure, extending the current version that is a measure of realization. This may require additional work to fit a prediction model on patent citation curves.

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 the sum of one plus scaled citations received by all the patents that were granted to that firm. Formally, $$\textit{Citation-Weighted Patents}_{f,t} = \frac{\sum_{j \in P_{f,t}} (1 + \frac{C_j}{\hat{C}_j})}{B_{f,t}},$$ 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 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 a firm's competitors which is defined as all the firms in the same industry (SIC3 level) excluding the 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 a firm's competitors which is defined as all the firms in the same industry (SIC3 level) excluding the firm itself, scaled by book assets. Formally in Kogan et al. (2017).
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. Compustat 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).
Patent Stock	The natural logarithm of the number of patents filed by the firm up to that year.
Firm Age	The natural logarithm of the age of the firm at the time that the investor filed its first patent application or entered the Compustat.
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 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, or 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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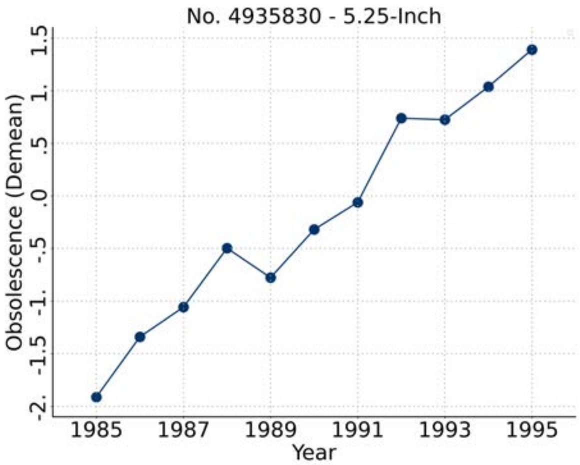
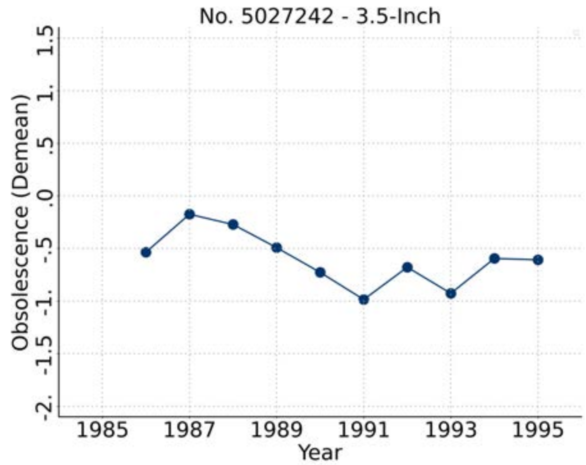
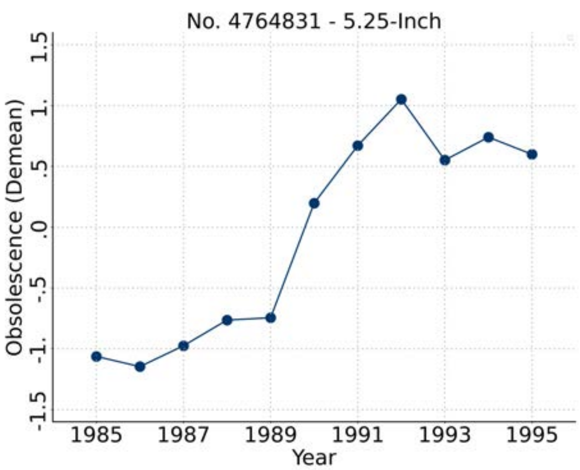


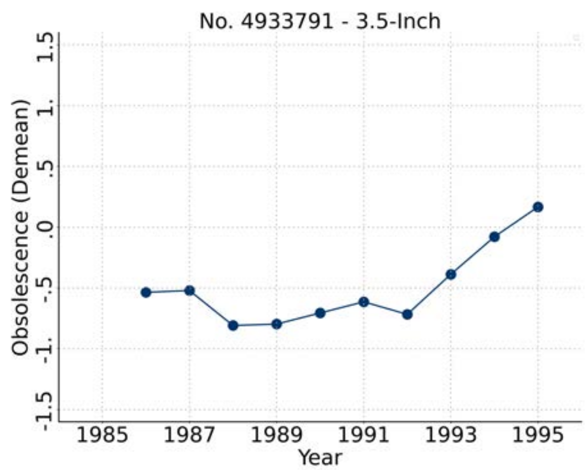
(a) 5.25-inch, US 4935830



(b) 3.5-inch, US 5027242



(c) 5.25-inch, US 4764831



(d) 3.5-inch, US 4933791

Figure 1. Obsolescence of Example HDD Patents

Notes. This figure plots the obsolescence measure for example HDD patents. Patent numbers and relevant HDD generations (5.25-in and 3.5-inch) are provided in the sub-figures.

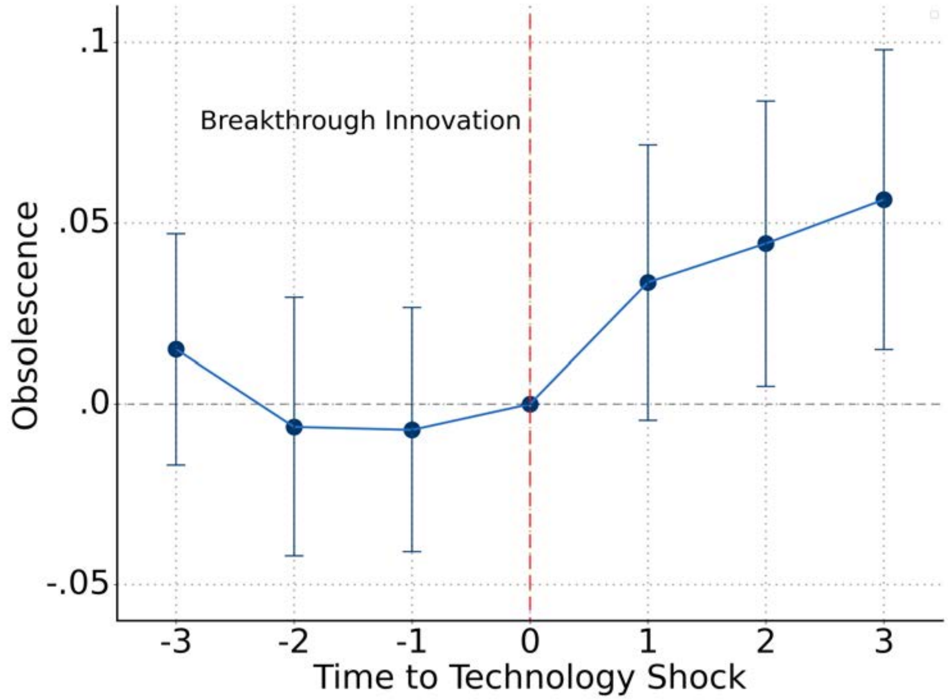
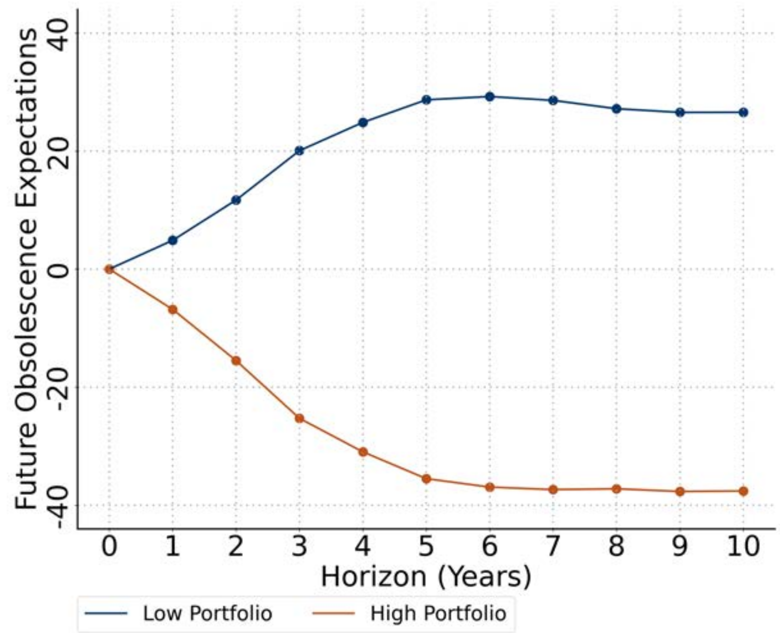
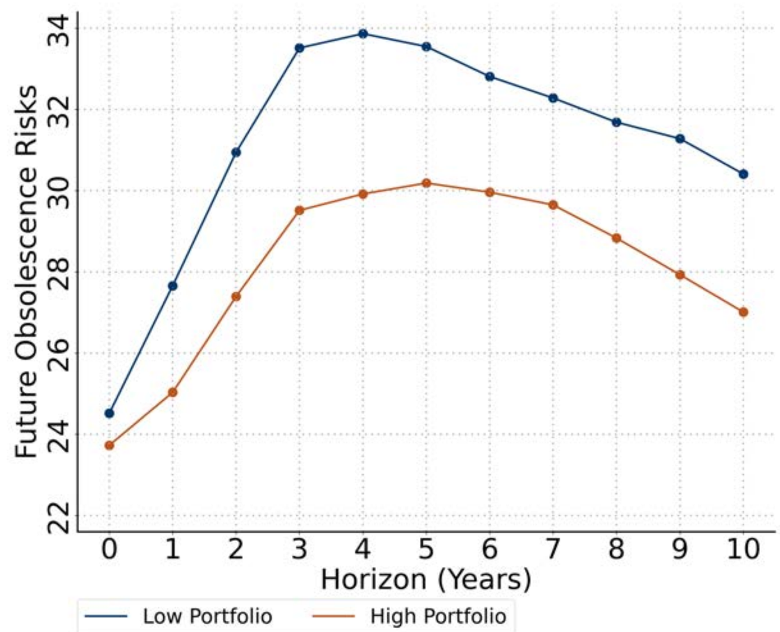


Figure 2. *Obsolescence* In Response to Breakthrough Innovation

Notes. This figure shows the change of *Technological Obsolescence* in firms that experience a breakthrough innovation in technology classes that the firm innovates in. The arrival of breakthrough innovation follows Kelly et al. (2021) who use textual information of patent filings.



(a) Average Future Technological Obsolescence



(b) Volatility of Future Technological Obsolescence

Figure 3. Realized *Obsolescence* and Future *Obsolescence* Risks

Notes. This figure shows future obsolescence of firms sorted using the current realized obsolescence (panel (a)), and the conditional volatility of technological obsolescence of those portfolios (panel (b)). Details of the portfolio construction is described in Section 3.1 of the main text.

Table 1. Firm-Year Level Summary Statistics of Innovation Measures

	count	mean	std	10%	25%	50%	75%	90%
Obsolescence, Horizon ω = 1 (%)	32,697	7.843	13.384	-8.039	-0.414	7.438	15.667	24.201
Obsolescence, Horizon ω = 3 (%)	32,697	12.900	26.557	-19.860	-3.336	13.346	29.456	44.765
Obsolescence, Horizon ω = 5 (%)	32,697	19.390	34.965	-22.924	-1.626	19.065	40.465	62.388
Obsolescence, Horizon ω = 10 (%)	30,644	34.126	51.844	-28.776	0.867	32.694	65.796	100.857
Stock Market-Based Patent Value (SM) (%)	32,697	15.322	33.402	0.000	0.251	3.699	15.612	41.488
Citation-Weighted Patents (CW) (%)	32,697	7.788	20.317	0.000	0.095	1.484	5.926	17.737
Competitors' Patent Value (%)	31,107	26.301	32.828	1.397	6.466	18.629	32.218	51.627
Competitors' Citation-Weighted Patents (%)	31,107	3.027	2.684	0.227	0.786	2.135	4.718	7.111

Notes. This table summarizes firm innovation characteristics. *Obsolescence* measures 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 citations received by the patents for which a firm applies, and subsequently receives, 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 variations of the *Obsolescence* (abbreviated as *Obs* here for compact notation) 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 Technological Obsolescence

	(1)	(2)	(3)	(4)
	Obsolescence			
Firm's Own New Patent Value	0.056***	0.091***	0.085***	0.106***
	(0.011)	(0.016)	(0.016)	(0.020)
Competitors' Patent Value	0.055**	0.047*	0.010	0.024
	(0.021)	(0.026)	(0.042)	(0.036)
Upstream Effects of Innovation	0.045*	0.056**		
	(0.026)	(0.028)		
Economy-Wide Index of Innovation			0.110**	0.097**
			(0.050)	(0.039)
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 correlations between the *Obsolescence* measure and potential sources of new innovation, including a 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. All right-hand-side variables are standardized to unit standard deviation to facilitate magnitude interpretations. 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 4. Firm-Year Level Summary Statistics

	count	mean	std	10%	25%	50%	75%	90%
Profits, Growth Rate (%)	29,734	4.132	29.619	-24.287	-6.369	4.575	15.529	32.280
Output, Growth Rate (%)	31,261	3.859	31.495	-23.109	-6.019	4.215	14.769	31.487
Capital, Growth Rate (%)	31,995	6.173	19.795	-8.377	0.140	5.520	12.547	23.869
Labor, Growth Rate (%)	31,654	2.021	21.017	-16.705	-5.214	1.660	9.672	22.314
TFP, Growth Rate (%)	23,816	-0.810	25.809	-24.321	-9.866	-0.415	9.179	22.835
Profits	32,689	2,190.551	5,878.533	7.211	48.198	260.424	1,269.023	5,200.971
Output	32,290	6,285.039	16,637.534	27.631	132.315	723.575	3,759.987	15,723.396
Capital	32,596	4,388.214	15,874.031	11.279	44.204	259.103	1,774.540	8,185.197
Labor	32,342	17.702	41.084	0.133	0.520	2.867	13.500	47.313
TFP	25,055	-0.336	0.448	-0.798	-0.539	-0.332	-0.113	0.165
Patent Stock	32,697	599.323	1,998.837	15	25	59	243	1,164
Firm Age	32,697	28.374	15.646	11	16	25	38	49
Idiosyncratic Volatility	32,623	0.001	0.002	0	0	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 Stock is the number of patents filed by the firm up to that year (noting the right truncation problem); Firm Age is the age of the firm at the time that the investor field its first patent application or entered the Compustat. 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. Technological Obsolescence and Firm Growth

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.011***	-0.017***	-0.021***	-0.025***	-0.031***
	(0.003)	(0.004)	(0.007)	(0.009)	(0.011)
			Output		
$Obsolescence_t$	-0.010***	-0.017***	-0.022***	-0.026**	-0.032**
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
			Capital		
$Obsolescence_t$	-0.012***	-0.023***	-0.033***	-0.043***	-0.052***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.012)
			Labor		
$Obsolescence_t$	-0.006***	-0.012***	-0.017**	-0.018**	-0.019*
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
			TFP		
$Obsolescence_t$	-0.008***	-0.012***	-0.014***	-0.015***	-0.014**
	(0.003)	(0.004)	(0.005)	(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 TFP, all defined and described in Table 4. The table presents results estimated using up to five years from t. Controls include 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, the log value of the firm age, 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. Technological Obsolescence and Growth, Controlling For Innovation Measures

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.010***	-0.016***	-0.019***	-0.023***	-0.026**
	(0.002)	(0.004)	(0.007)	(0.009)	(0.011)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.001	-0.004	-0.005	-0.001	0.014
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
$Patent\ Value_t$ (SM)	0.022***	0.032***	0.041**	0.048***	0.054***
	(0.007)	(0.012)	(0.017)	(0.018)	(0.019)
			Output		
$Obsolescence_t$	-0.009***	-0.016***	-0.021**	-0.024**	-0.029**
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006	-0.010	-0.020**	-0.019	-0.012
	(0.004)	(0.007)	(0.010)	(0.012)	(0.015)
$Patent\ Value_t$ (SM)	0.020***	0.031**	0.039**	0.045**	0.050**
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
$Obsolescence_t$	-0.011***	-0.022***	-0.031***	-0.041***	-0.049***
	(0.002)	(0.005)	(0.008)	(0.010)	(0.012)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.009***	-0.013***	-0.015***	-0.014*	-0.015
	(0.002)	(0.003)	(0.005)	(0.008)	(0.010)
$Patent\ Value_t$ (SM)	0.019***	0.033***	0.041***	0.047***	0.051***
	(0.004)	(0.009)	(0.012)	(0.016)	(0.018)
			Labor		
$Obsolescence_t$	-0.006***	-0.011**	-0.016**	-0.017**	-0.017*
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006**	-0.010**	-0.012*	-0.013	-0.013
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$ (SM)	0.013***	0.022***	0.026***	0.031**	0.033**
	(0.004)	(0.007)	(0.010)	(0.013)	(0.014)
			TFP		
$Obsolescence_t$	-0.007***	-0.011***	-0.012***	-0.013***	-0.011*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.002	0.003	0.004	0.001	0.009
	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
$Patent\ Value_t$ (SM)	0.015**	0.021*	0.026**	0.031***	0.036***
	(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			
$Obsolescence_t$	-0.017***	-0.006	-0.022***	-0.007	-0.021***	-0.018
	(0.006)	(0.006)	(0.007)	(0.005)	(0.007)	(0.015)
			Output			
$Obsolescence_t$	-0.020***	-0.005	-0.022***	-0.010**	-0.025***	-0.010
	(0.007)	(0.007)	(0.008)	(0.005)	(0.009)	(0.012)
			Capital			
$Obsolescence_t$	-0.030***	-0.015**	-0.034***	-0.010**	-0.039***	-0.005
	(0.007)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
			Labor			
$Obsolescence_t$	-0.013**	-0.008	-0.018***	-0.005	-0.020***	-0.001
	(0.006)	(0.006)	(0.007)	(0.004)	(0.008)	(0.010)
			TFP			
$Obsolescence_t$	-0.012***	-0.006	-0.014***	-0.009**	-0.015***	-0.009
	(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 all the firm's 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. Technological Obsolescence and Competitor Innovation Measures

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.010***	-0.014***	-0.019**	-0.023**	-0.030***
	(0.003)	(0.004)	(0.007)	(0.009)	(0.012)
Patent Value$_t$	0.020***	0.029***	0.037**	0.045***	0.053***
	(0.007)	(0.011)	(0.015)	(0.016)	(0.017)
Competitors' Patent Value$_t$	-0.013	-0.036*	-0.050*	-0.057	-0.064
	(0.013)	(0.022)	(0.030)	(0.041)	(0.049)
			Output		
$Obsolescence_t$	-0.009***	-0.015***	-0.019**	-0.023**	-0.028**
	(0.003)	(0.005)	(0.008)	(0.011)	(0.014)
Patent Value$_t$	0.016***	0.025**	0.030**	0.036*	0.042**
	(0.006)	(0.011)	(0.013)	(0.019)	(0.019)
Competitors' Patent Value$_t$	-0.020	-0.039	-0.061*	-0.082*	-0.101**
	(0.015)	(0.025)	(0.033)	(0.044)	(0.047)
			Capital		
$Obsolescence_t$	-0.011***	-0.020***	-0.030***	-0.041***	-0.051***
	(0.002)	(0.005)	(0.008)	(0.010)	(0.013)
Patent Value$_t$	0.015***	0.026***	0.032***	0.037***	0.040***
	(0.003)	(0.007)	(0.011)	(0.014)	(0.015)
Competitors' Patent Value$_t$	-0.027**	-0.052**	-0.085**	-0.107**	-0.129**
	(0.011)	(0.022)	(0.034)	(0.043)	(0.053)
			Labor		
$Obsolescence_t$	-0.005**	-0.009**	-0.013*	-0.015*	-0.016
	(0.002)	(0.005)	(0.007)	(0.009)	(0.010)
Patent Value$_t$	0.010***	0.016***	0.019**	0.022**	0.024**
	(0.003)	(0.006)	(0.008)	(0.010)	(0.012)
Competitors' Patent Value$_t$	-0.021**	-0.042**	-0.072**	-0.091**	-0.107**
	(0.009)	(0.018)	(0.029)	(0.040)	(0.047)
			TFP		
$Obsolescence_t$	-0.007**	-0.012***	-0.014***	-0.015***	-0.014**
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
Patent Value$_t$	0.013	0.019	0.024**	0.030***	0.036***
	(0.008)	(0.013)	(0.012)	(0.011)	(0.011)
Competitors' Patent Value$_t$	-0.025**	-0.036*	-0.035**	-0.028	-0.026
	(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. Monthly Returns of Obsolescence-Sorted Portfolios

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 technological 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), and the factor models that replace the traditional Fama-French HML factor with the intangible-adjusted HML (Eisfeldt, Kim, and Papanikolaou, 2020). In panels (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 parentheses.

Table 10. Technological Obsolescence and Forecasting Errors

	(1)	(2)	(3)	(4)
	$(\pi_{f,t+1} - F_t\pi_{f,t+1})/P_{f,t-1}$		$(\pi_{f,t+2} - F_t\pi_{f,t+2})/P_{f,t-1}$	
Obsolescence	-0.361**	-0.458***	-0.510**	-0.693***
	(0.148)	(0.149)	(0.203)	(0.206)
Observations	23,039	23,039	20,792	20,792
R-squared	0.003	0.005	0.006	0.010
New Innovation Control	No	Yes	No	Yes

Notes. This table reports the results from regressing firm-level EPS forecast errors on *Obsolescence* based on equation (3). The dependent variables are the forecast errors based on the consensus one-year and two-year forecasts for the current fiscal year earnings, that is, $(\pi_{f,t+\tau} - F_t\pi_{f,t+\tau})/P_{f,t-1}$ for $\tau = 1,2$. 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.

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 usually increases in the early years as the new technology starts to diffuse and be adopted; it later decays as the technology fails to stay at the frontier and becomes replaced by newer generations of technology. This conceptual idea has been discussed in many classic works on innovation (Pakes and Schankerman, 1984; Caballero and Jaffe, 1993).

Annual citations received by each patent capture knowledge aging.[18] 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. This figure shows that new patents rely heavily on patents that are less than 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 impacts and may be influential even after 50 years, suggesting heterogeneity in the speed of aging.

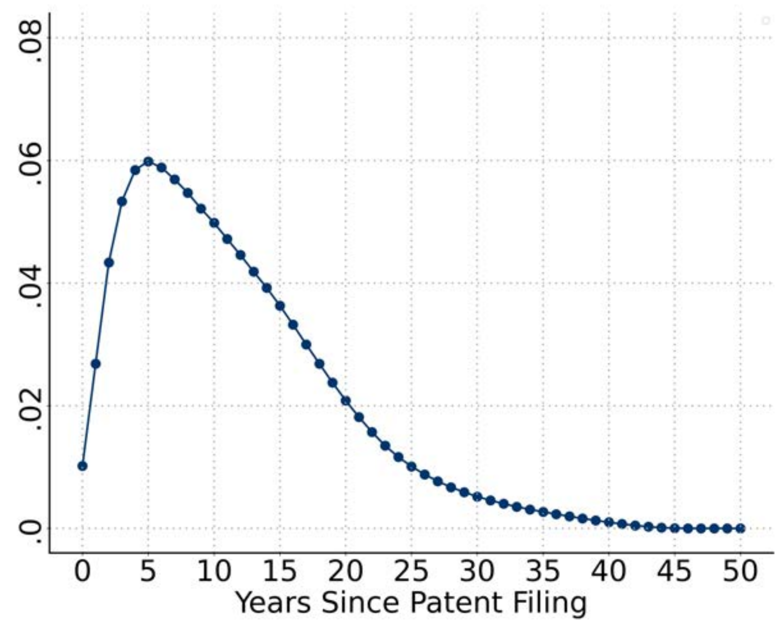
In Figure A.2, we perform the reverse exercise to show the same point. In panel (a), we study the forward citations each patent receives through its life cycle. Because of the right-truncation problem of patent citations, we produce the citation dynamic curve by cohorts of patent filing years. Patents 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 more quickly.

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

[18]This intuition is also used in bibliometrics and scientometrics, in which in use citation patterns to patents and papers to track technology evolution.

for the sample of patents 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).

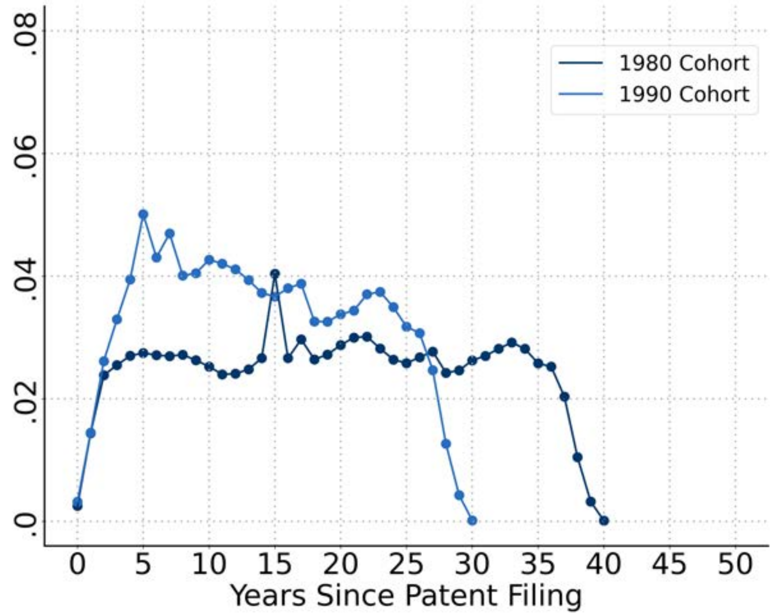
One caveat is that the process of citing patents could be noisy (Roach and Cohen, 2013). Most noticeably, a large portion of citations are so-called examiner-citations, which are inserted by patent examiners but not the patent applicants or their hired professionals (Alcácer, Gittelman, and Sampat, 2009). 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 the 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.



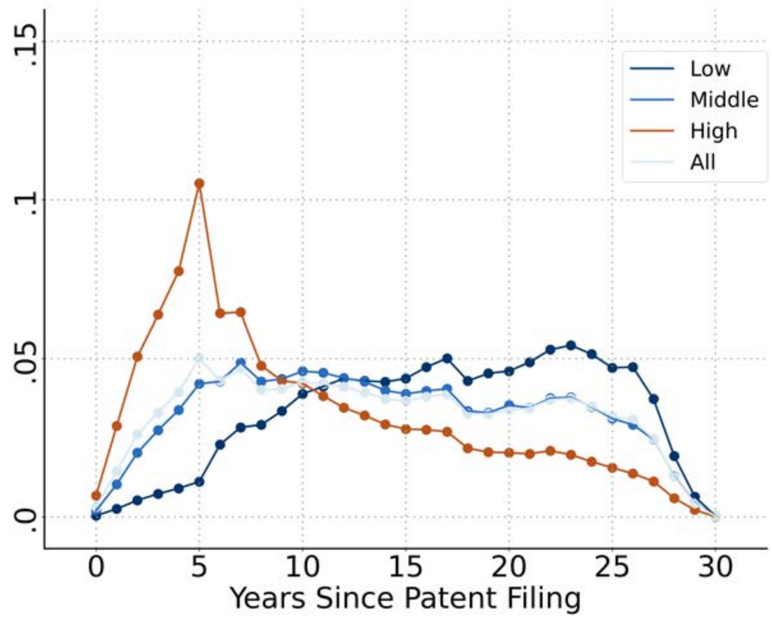
(a) Average Backward Citation Dynamic

Figure A.1. Patent Backward and Forward Citation Dynamics

Notes. This figure plots distributions of backward citation lags. Specifically, 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 for which 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.

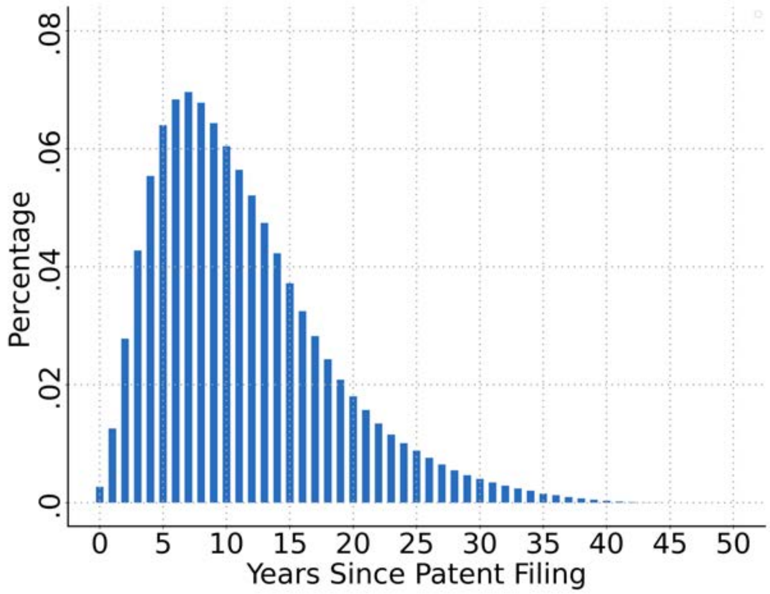


Figure A.3. Distribution of Patents' Half-Lives

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.

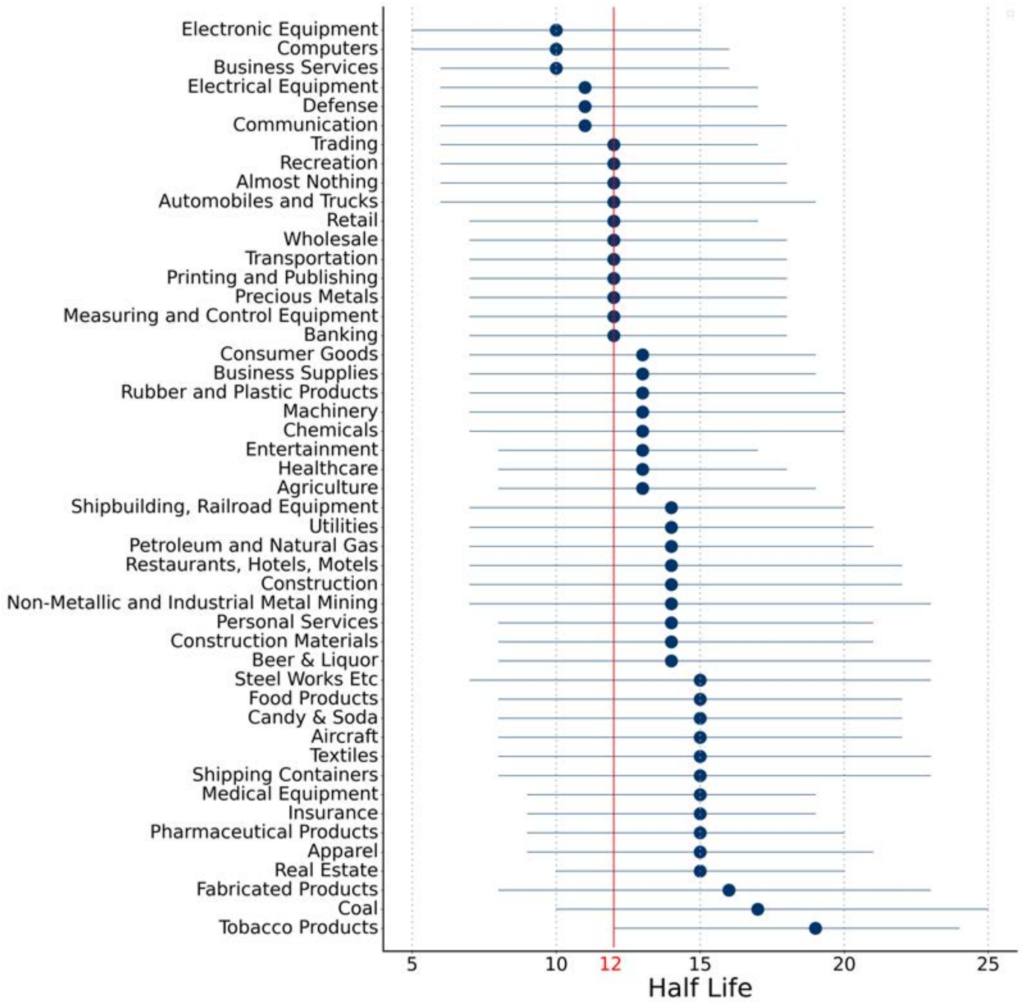


Figure A.4. Dynamics of Citations Received By Each Patent—Heterogeneity

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

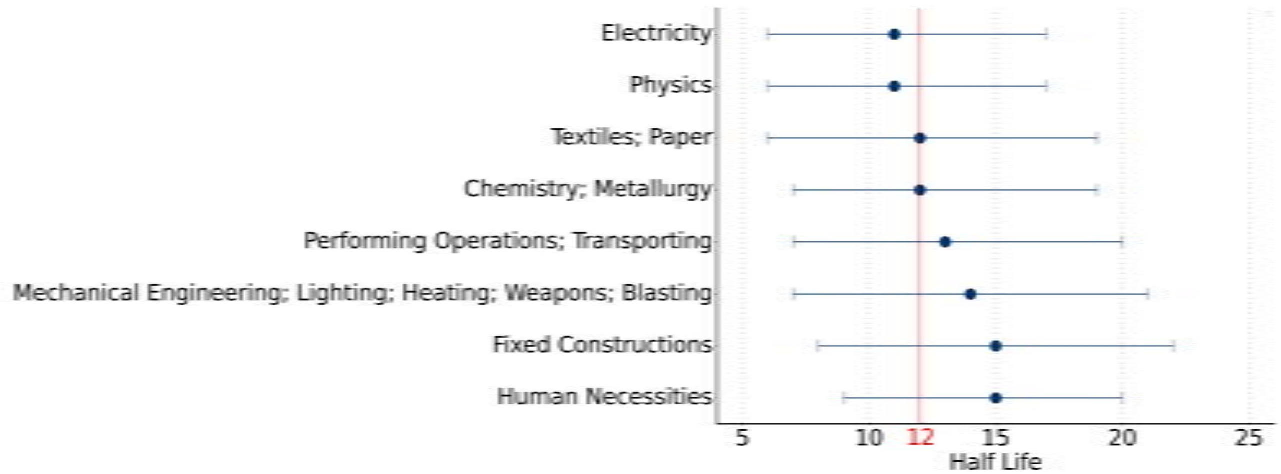
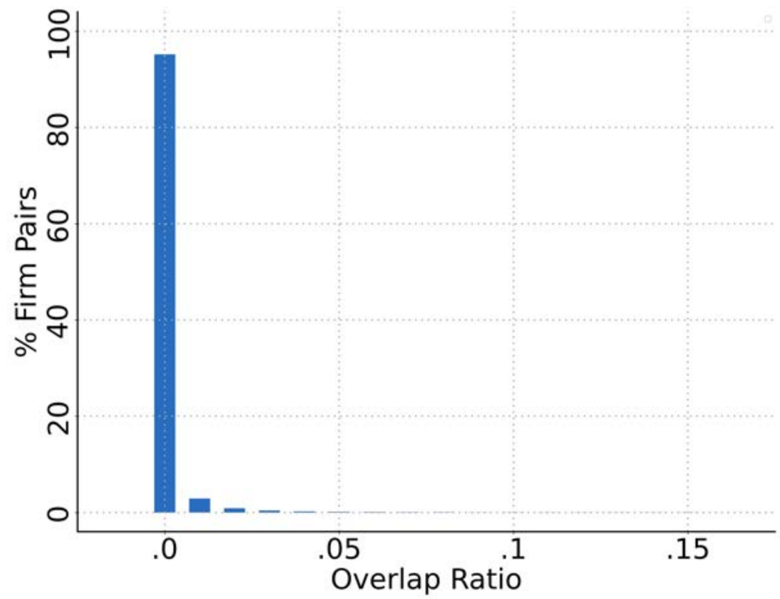
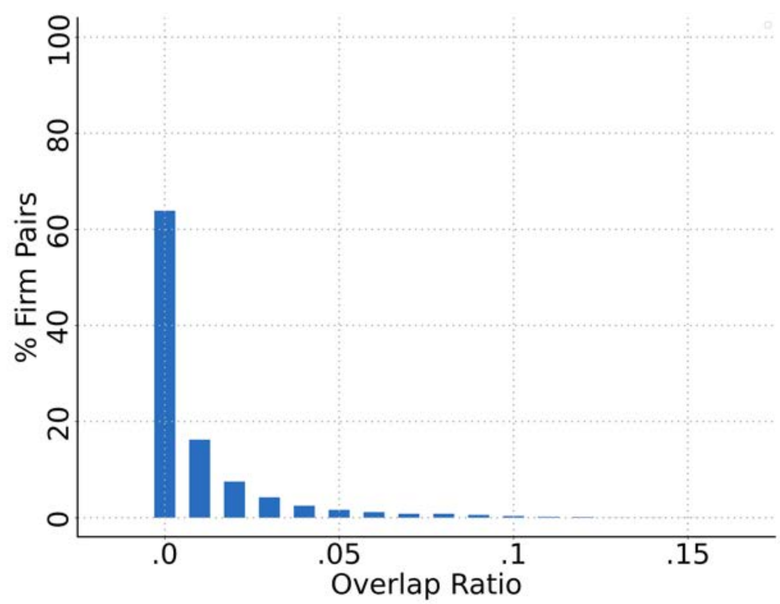


Figure A.5. Patent Citation Half-Lives By International Patent Classification Categories

A.2. Additional Results



(a) All Firms with Patents



(b) Firms with >100 Patents

Figure A.6. 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 firm i and j's bases are calculated as the ratio between the size of their intersections (numerator) and the size of their unions (denominator). Panel (a) uses all firms with a patent, while panel (b) focuses on firms with at least 100 patents.

Table A.1. Robustness of Obsolescence Measure - Horizons ω = 1

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.005*	-0.009**	-0.016***	-0.019***	-0.022***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.000	-0.003	-0.003	0.001	0.016
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.022***	0.033***	0.042**	0.048***	0.055***
	(0.008)	(0.012)	(0.017)	(0.018)	(0.019)
			Output		
$Obsolescence_t$	-0.008***	-0.011***	-0.018***	-0.023***	-0.032***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.009	-0.019*	-0.017	-0.010
	(0.004)	(0.007)	(0.010)	(0.013)	(0.015)
Patent Value$_t$ (SM)	0.020***	0.031**	0.039**	0.045**	0.051**
	(0.007)	(0.013)	(0.016)	(0.022)	(0.020)
			Capital		
$Obsolescence_t$	-0.010***	-0.015***	-0.020***	-0.026***	-0.036***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.012***	-0.013**	-0.011	-0.012
	(0.002)	(0.003)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.019***	0.034***	0.042***	0.048***	0.053***
	(0.004)	(0.009)	(0.013)	(0.017)	(0.018)
			Labor		
$Obsolescence_t$	-0.006***	-0.011***	-0.014***	-0.021***	-0.024***
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.006**	-0.009*	-0.011	-0.012	-0.012
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.013***	0.022***	0.027***	0.032**	0.034**
	(0.004)	(0.007)	(0.010)	(0.013)	(0.014)
			TFP		
$Obsolescence_t$	-0.002	-0.004	-0.006	-0.011***	-0.014***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Citation-Weighted Patents$_t$ (CW)	-0.001	0.005	0.006	0.002	0.010
	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015**	0.022*	0.026**	0.032***	0.037***
	(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$_t$	-0.007**	-0.014***	-0.019***	-0.022***	-0.023**
	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.001	-0.003	-0.004	0.000	0.015
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.022***	0.032***	0.041**	0.048***	0.055***
	(0.007)	(0.012)	(0.017)	(0.018)	(0.019)
			Output		
Obsolescence$_t$	-0.007**	-0.013***	-0.021***	-0.025***	-0.028***
	(0.003)	(0.004)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.010	-0.019*	-0.018	-0.011
	(0.004)	(0.007)	(0.010)	(0.013)	(0.015)
Patent Value$_t$ (SM)	0.020***	0.031**	0.039**	0.045**	0.050**
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
Obsolescence$_t$	-0.009***	-0.017***	-0.026***	-0.037***	-0.045***
	(0.002)	(0.004)	(0.006)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.012***	-0.014**	-0.012	-0.013
	(0.002)	(0.003)	(0.005)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.019***	0.034***	0.042***	0.047***	0.052***
	(0.004)	(0.009)	(0.013)	(0.016)	(0.018)
			Labor		
Obsolescence$_t$	-0.006***	-0.011***	-0.017***	-0.020**	-0.020**
	(0.002)	(0.004)	(0.006)	(0.008)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.006**	-0.009**	-0.012*	-0.013	-0.013
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.013***	0.022***	0.026***	0.031**	0.033**
	(0.004)	(0.007)	(0.010)	(0.013)	(0.014)
			TFP		
Obsolescence$_t$	-0.004	-0.009**	-0.012***	-0.016***	-0.015***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Citation-Weighted Patents$_t$ (CW)	-0.002	0.004	0.005	0.001	0.009
	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015**	0.022*	0.026**	0.032***	0.037***
	(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. Technological Obsolescence and Firm Distress and Failure

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Obsolescence$_t$	0.0001	0.0007	0.0016*	0.0021*	0.0022
	(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$_t$	-0.015**	-0.005	-0.020***	-0.006	-0.019***	-0.017
	(0.006)	(0.006)	(0.007)	(0.005)	(0.007)	(0.015)
Citation-Weighted Patents$_t$ (CW)	-0.004	-0.003	-0.005	-0.003	-0.008	0.005
	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)
Patent Value$_t$ (SM)	0.041**	0.042**	0.041**	0.041**	0.043**	0.049***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.012)
			Output			
Obsolescence$_t$	-0.019**	-0.005	-0.021***	-0.009*	-0.024**	-0.008
	(0.008)	(0.007)	(0.008)	(0.005)	(0.009)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.020*	-0.019*	-0.020**	-0.019*	-0.027**	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)
Patent Value$_t$ (SM)	0.039**	0.040**	0.039**	0.039**	0.042**	0.042***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.012)
			Capital			
Obsolescence$_t$	-0.027***	-0.015**	-0.032***	-0.009*	-0.037***	-0.005
	(0.007)	(0.006)	(0.008)	(0.005)	(0.008)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.014***	-0.013**	-0.015***	-0.013**	-0.016***	-0.016
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.011)
Patent Value$_t$ (SM)	0.041***	0.042***	0.041***	0.042***	0.043***	0.046***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)

Heterogeneity	Core Patents		Product/Process Patents		Competition	
	Core	Non-Core	Product	Process	High	Low
			Labor			
Obsolescence$_t$	-0.012*	-0.007	-0.018**	-0.004	-0.019**	-0.000
	(0.006)	(0.006)	(0.007)	(0.005)	(0.008)	(0.011)
Citation-Weighted Patents$_t$ (CW)	-0.012*	-0.011	-0.012*	-0.011	-0.015**	-0.000
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.013)
Patent Value$_t$ (SM)	0.026***	0.027***	0.026***	0.027***	0.029***	0.025***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.009)
			TFP			
Obsolescence$_t$	-0.011**	-0.006	-0.012***	-0.007**	-0.013***	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)
Citation-Weighted Patents$_t$ (CW)	0.005	0.006	0.004	0.005	0.002	0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)
Patent Value$_t$ (SM)	0.026**	0.026**	0.026**	0.026**	0.030**	0.007
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(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 all the firm's 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		
	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
Labor						
$Obsolescence_t$	-0.008***	-0.016**	-0.026***	-0.007***	-0.014**	-0.014
	(0.002)	(0.006)	(0.009)	(0.002)	(0.006)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.001	-0.004	0.015	-0.001	-0.003	0.016
	(0.004)	(0.011)	(0.016)	(0.004)	(0.011)	(0.016)
Patent Value$_t$ (SM)	0.022***	0.041**	0.054***	0.022***	0.041**	0.055***
	(0.007)	(0.017)	(0.019)	(0.007)	(0.017)	(0.019)
Output						
$Obsolescence_t$	-0.005**	-0.015**	-0.023**	-0.008***	-0.015**	-0.012
	(0.002)	(0.007)	(0.011)	(0.002)	(0.006)	(0.011)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.019*	-0.011	-0.005	-0.019*	-0.010
	(0.004)	(0.010)	(0.015)	(0.004)	(0.010)	(0.015)
Patent Value$_t$ (SM)	0.020***	0.039**	0.050**	0.020***	0.039**	0.051**
	(0.007)	(0.016)	(0.020)	(0.007)	(0.016)	(0.020)
Capital						
$Obsolescence_t$	-0.009***	-0.022***	-0.037***	-0.008***	-0.016***	-0.023***
	(0.002)	(0.007)	(0.011)	(0.002)	(0.005)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.013**	-0.013	-0.009***	-0.013**	-0.012
	(0.002)	(0.005)	(0.010)	(0.002)	(0.006)	(0.010)
Patent Value$_t$ (SM)	0.019***	0.041***	0.051***	0.019***	0.042***	0.053***
	(0.004)	(0.013)	(0.018)	(0.004)	(0.013)	(0.018)

	High-Generality Patents			Low-Generality Patents		
	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
			Labor			
Obsolescence$_t$	-0.005***	-0.013**	-0.017**	-0.005***	-0.013**	-0.011
	(0.002)	(0.006)	(0.009)	(0.002)	(0.005)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.006**	-0.012*	-0.013	-0.006**	-0.012*	-0.012
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.011)
Patent Value$_t$ (SM)	0.013***	0.026***	0.033**	0.013***	0.026***	0.034**
	(0.004)	(0.010)	(0.014)	(0.004)	(0.010)	(0.014)
			TFP			
Obsolescence$_t$	-0.009***	-0.011**	-0.014**	-0.006***	-0.009**	-0.002
	(0.003)	(0.004)	(0.006)	(0.002)	(0.004)	(0.005)
Citation-Weighted Patents$_t$ (CW)	-0.002	0.005	0.009	-0.002	0.006	0.010
	(0.004)	(0.007)	(0.009)	(0.004)	(0.007)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.026**	0.036***	0.015*	0.026**	0.037***
	(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 technology base is constructed using patents that are of high- vs. low- generality defined as in Hall, Jaffe, and Trajtenberg (2001). The empirical design follows that in Table 5, only the $t+1$, $t+3$, and $t+5$ 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									
$Obsolescence_t$	-0.008***	-0.019***	-0.029***	-0.007***	-0.008	-0.010	-0.002	-0.017	-0.037**
	(0.002)	(0.006)	(0.008)	(0.002)	(0.006)	(0.010)	(0.005)	(0.011)	(0.016)
Citation-Weighted Patents$_t$ (CW)	-0.002	-0.004	0.011	-0.003	-0.008	0.005	-0.011	-0.033	-0.005
	(0.004)	(0.011)	(0.016)	(0.005)	(0.013)	(0.019)	(0.012)	(0.024)	(0.037)
Patent Value$_t$ (SM)	0.022***	0.041**	0.055***	0.025***	0.046***	0.061***	0.042***	0.082**	0.124***
	(0.008)	(0.017)	(0.019)	(0.008)	(0.018)	(0.020)	(0.011)	(0.033)	(0.045)
Output									
$Obsolescence_t$	-0.008**	-0.018**	-0.029***	-0.006***	-0.011	-0.010	-0.004	-0.017*	-0.040**
	(0.003)	(0.008)	(0.011)	(0.002)	(0.007)	(0.010)	(0.004)	(0.010)	(0.016)
Citation-Weighted Patents$_t$ (CW)	-0.006*	-0.022**	-0.015	-0.007	-0.031**	-0.029	-0.006	-0.019	-0.001
	(0.004)	(0.010)	(0.016)	(0.005)	(0.012)	(0.018)	(0.007)	(0.018)	(0.028)
Patent Value$_t$ (SM)	0.020***	0.039**	0.051**	0.024***	0.045***	0.059***	0.038***	0.083***	0.118***
	(0.007)	(0.016)	(0.020)	(0.007)	(0.017)	(0.022)	(0.012)	(0.032)	(0.042)
Capital									
$Obsolescence_t$	-0.010***	-0.027***	-0.042***	-0.006***	-0.017***	-0.023***	-0.008*	-0.020**	-0.027*
	(0.002)	(0.006)	(0.009)	(0.002)	(0.005)	(0.009)	(0.004)	(0.010)	(0.016)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.015***	-0.017*	-0.010***	-0.015**	-0.020	-0.007	-0.010	0.003
	(0.002)	(0.005)	(0.010)	(0.002)	(0.007)	(0.012)	(0.005)	(0.017)	(0.027)
Patent Value$_t$ (SM)	0.019***	0.042***	0.052***	0.021***	0.046***	0.060***	0.037***	0.086***	0.121***
	(0.004)	(0.013)	(0.019)	(0.004)	(0.013)	(0.019)	(0.009)	(0.027)	(0.037)

	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$_t$	-0.005***	-0.014***	-0.016*	-0.005***	-0.010*	-0.006	-0.002	-0.016**	-0.036***
	(0.002)	(0.005)	(0.008)	(0.002)	(0.005)	(0.008)	(0.003)	(0.008)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.007**	-0.013*	-0.014	-0.007**	-0.016**	-0.021	-0.015***	-0.035**	-0.057**
	(0.003)	(0.007)	(0.012)	(0.003)	(0.008)	(0.014)	(0.004)	(0.014)	(0.023)
Patent Value$_t$ (SM)	0.013***	0.026***	0.034**	0.014***	0.029***	0.038***	0.027***	0.066***	0.094***
	(0.004)	(0.010)	(0.014)	(0.003)	(0.010)	(0.015)	(0.009)	(0.024)	(0.030)
					TFP				
Obsolescence$_t$	-0.008***	-0.015***	-0.017***	-0.005*	-0.002	-0.004	-0.004	-0.015*	-0.016
	(0.002)	(0.003)	(0.006)	(0.003)	(0.004)	(0.006)	(0.006)	(0.009)	(0.014)
Citation-Weighted Patents$_t$ (CW)	-0.003	0.005	0.007	-0.001	0.006	0.009	-0.017*	0.000	0.003
	(0.004)	(0.007)	(0.010)	(0.005)	(0.008)	(0.012)	(0.009)	(0.016)	(0.033)
Patent Value$_t$ (SM)	0.015*	0.026**	0.036***	0.019**	0.031**	0.040***	0.042***	0.062***	0.081***
	(0.008)	(0.012)	(0.010)	(0.009)	(0.012)	(0.012)	(0.010)	(0.018)	(0.024)

Notes. This table examines the relation between *Obsolescence* calculated using sub-components of the technology base and firm growth and productivity. Three different components are used in the technology base: 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). The empirical design follows that in Table 5, only the $t+1$, $t+3$, and $t+5$ 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		
$Obsolescence_t$	-0.011***	-0.020***	-0.029***	-0.034***	-0.039***
	(0.002)	(0.005)	(0.006)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.002	-0.006	-0.007	-0.003	0.011
	(0.004)	(0.007)	(0.011)	(0.014)	(0.016)
$Patent\ Value_t$ (SM)	0.021***	0.030***	0.038**	0.045***	0.051***
	(0.007)	(0.012)	(0.016)	(0.017)	(0.018)
			Output		
$Obsolescence_t$	-0.009***	-0.016***	-0.021***	-0.019**	-0.018*
	(0.003)	(0.005)	(0.007)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006*	-0.011	-0.021**	-0.019	-0.012
	(0.004)	(0.007)	(0.010)	(0.013)	(0.015)
$Patent\ Value_t$ (SM)	0.019***	0.030**	0.037**	0.044**	0.049**
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
$Obsolescence_t$	-0.013***	-0.022***	-0.029***	-0.031***	-0.033***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.010***	-0.014***	-0.016***	-0.015*	-0.016
	(0.002)	(0.003)	(0.006)	(0.008)	(0.010)
$Patent\ Value_t$ (SM)	0.018***	0.032***	0.040***	0.046***	0.050***
	(0.004)	(0.008)	(0.012)	(0.016)	(0.017)
			Labor		
$Obsolescence_t$	-0.005***	-0.009**	-0.012**	-0.014*	-0.016*
	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006**	-0.010**	-0.013*	-0.014	-0.014
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$ (SM)	0.013***	0.021***	0.025***	0.030**	0.033**
	(0.003)	(0.007)	(0.010)	(0.012)	(0.014)
			TFP		
$Obsolescence_t$	-0.006**	-0.012***	-0.015***	-0.012**	-0.013*
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.002	0.003	0.004	0.001	0.008
	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
$Patent\ Value_t$ (SM)	0.015*	0.020	0.025**	0.031***	0.035***
	(0.008)	(0.013)	(0.011)	(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. We use the technological obsolescence as the rate of change in citations made to the firm's own patent portfolio, instead of technology base. The design follows that in Table 5.

Table A.8. Robustness of *Obsolescence* Measure—Duplicated Technology Base

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits		
$Obsolescence_t$	-0.009***	-0.014***	-0.017***	-0.022***	-0.025**
	(0.003)	(0.004)	(0.007)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.001	-0.004	-0.004	-0.001	0.014
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
$Patent\ Value_t$ (SM)	0.022***	0.032***	0.041**	0.048***	0.054***
	(0.007)	(0.012)	(0.017)	(0.018)	(0.019)
			Output		
$Obsolescence_t$	-0.009***	-0.016***	-0.019**	-0.021**	-0.025**
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006	-0.010	-0.020**	-0.018	-0.012
	(0.004)	(0.007)	(0.010)	(0.012)	(0.015)
$Patent\ Value_t$ (SM)	0.020***	0.031**	0.039**	0.045**	0.050**
	(0.007)	(0.013)	(0.016)	(0.021)	(0.020)
			Capital		
$Obsolescence_t$	-0.011***	-0.020***	-0.028***	-0.037***	-0.045***
	(0.002)	(0.004)	(0.007)	(0.009)	(0.012)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.009***	-0.013***	-0.014***	-0.014*	-0.015
	(0.002)	(0.003)	(0.005)	(0.008)	(0.010)
$Patent\ Value_t$ (SM)	0.019***	0.033***	0.041***	0.047***	0.051***
	(0.004)	(0.009)	(0.013)	(0.017)	(0.018)
			Labor		
$Obsolescence_t$	-0.005**	-0.010**	-0.014**	-0.015*	-0.016
	(0.002)	(0.004)	(0.007)	(0.008)	(0.010)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.006**	-0.010**	-0.012*	-0.013	-0.013
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$ (SM)	0.013***	0.022***	0.026***	0.031**	0.033**
	(0.004)	(0.007)	(0.010)	(0.013)	(0.014)
			TFP		
$Obsolescence_t$	-0.006**	-0.010***	-0.012***	-0.013***	-0.011*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.002	0.003	0.005	0.001	0.009
	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
$Patent\ Value_t$ (SM)	0.015**	0.022*	0.026**	0.032***	0.036***
	(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. We use duplicated technology base to construct the technological obsolescence; that is, we allow the same patent to appear multiple times in the technology base if it was cited multiple times by different patents of this firm. The design follows that in Table 5.

Table A.9. 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 3 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 an *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, and High——based on the 30th and 70th percentile in *Obsolescence* in year $t-1$. Detailed variable definitions are provided in the Appendix.

Table A.10. Return Predictive Power of Technological 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 analyses follow Table 9 in the main text.

Table A.11. Return Predictive Power of Technological 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)) and 125 size/BM/Mom-adjusted returns (Size/BM/Momentum-adjret, (Daniel et al., 1997)).

Table A.12. Return Predictive Power of Technological 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 being 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 9. Standard errors are reported in parenthesis.

Table A.13. Return Predictive Power of Technological 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* measures 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 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 are the natural logarithms 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.

Table A.14. Return Predictive Power of Technological 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).