TECHNOLOGICAL OBSOLESCENCE

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(Forthcoming, *Review of Financial Studies*)

This paper proposes a new measure of technological obsolescence using detailed patent data. The measure contains incremental information about firm innovation relative to measures focusing on new innovation. 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 underperform 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.

Song Ma is with Yale University and the NBER. Working on this paper constantly reminds me of the joy and pain of working on a solo paper. I want to thank Itay Goldstein (the editor) and two anonymous referees whose helpful comments significantly improved the paper, and whose patience allowed me to revise the paper carefully. For continuous support, I want to thank my coauthors and numerous colleagues whose comments and discussions helped shape my thinking around this topic over the years. For detailed comments and discussions, I thank Nick Barberis, Shai Bernstein (discussant), Gilles Chemla (discussant), Wesley Cohen, Michael Ewens, Laurent Fresard, Stefano Giglio, Paul Goldsmith-Pinkham, Po-Hsuan Hsu, Allen Hu, Theis Jensen, Bryan Kelly, Leonid Kogan, Ernest Liu, Yueran Ma, Matt Marx, Stavros Panageas, Bruno Pellegrino (discussant), Lawrence Schmidt (discussant), Peter Schott, Bryan Seegmiller (discussant), Merih Sevilir (discussant), Kelly Shue, Janis Skrastins, Kaushik Vasudevan, Ting Xu (discussant), and Alex Zentefis. I also want to thank workshop participants at AFA, Bilkent, BlackRock, Bocconi, CKGSB, ESADE, FIRS (Budapest), FOM Annual Conference (Dartmouth), GSU CEAR Conference, Harvard, Illinois, LSE, Lugano, Michigan State, NBER Summer Institute (Macroeconomics and Productivity), PKU, Queen Mary, RUC, SFS Cavalcade (UNC), SMU, Toulouse School of Economics, Tulane, U Kentucky Finance Conference, UT Dallas, Warwick, Wisconsin, Yale (Economics). Xugan Chen provided excellent research assistance. All errors are my own. Please address correspondence to Song Ma, Yale School of Management, 165 Whitney Ave, New Haven, CT 06511. E-mail: song.ma@yale.edu.

The Schumpeterian narrative of creative destruction comprises two key components: creation and destruction. The more extensively studied component is the advent of new innovations. Creative innovations are developed and adopted, leading to an expansion in product variety, increased productivity within innovating firms, and ultimately, economic growth. Empirical research in this area has provided significant insights, leveraging our ability to track the emergence of new and novel innovations, most notably through widely accepted patent-based measures.[1]

In contrast, this paper focuses on the destruction pillar, which operates through technological obsolescence. Technological obsolescence refers to the process by which once-frontier technologies lose value as new technologies emerge. This study aims to deepen our understanding of technological obsolescence and its effects on firms and financial markets. We proceed in two steps. First, we develop and validate a novel measure of technological obsolescence (*Obsolescence*) at the firm-year level, which captures the declining relevance of a firm's existing patent portfolio. Second, we examine the relationship between technological obsolescence and future firm growth, productivity, and resource allocation, as well as how financial markets respond to the obsolescence of technologies.

There are two key motivations behind this exercise. First, there is an important conceptual distinction between technological obsolescence and new innovation. Obsolescence pertains to a firm's *existing* innovation portfolio (i.e., innovations that arrived in the past), rather than the arrival of new innovations. Given that annual new patents constitute only 6% of a firm's existing patent portfolio, it is crucial to understand how the value of the remaining 94% evolves. Additionally, obsolescence considers the dynamic value of technological innovations over time, rather than merely assessing their value at the time of arrival.

Second, while the positive role of innovation in firm profitability and economic growth is well-documented (e.g., KPSS), technological obsolescence is a more nuanced process that requires further exploration. In a broad set of endogenous growth models, creative destruction in the form of direct replacement by competitors suggests a sharp and often oversimplified "live-or-die" outcome from obsolescence (Grossman and Helpman, 1991; Aghion and Howitt, 1992; Klette and Kortum,

[1]Recent studies have combined patent information with stock market data upon patent approval (Kogan, Papanikolaou, Seru, and Stoffman, 2017, *hereafter* KPSS) or employed text-based methods (Bellstam, Bhagat, and Cookson, 2020; Kelly, Papanikolaou, Seru, and Taddy, 2021; Bowen III, Frésard, and Hoberg, 2023), achieving notable success in linking the arrival of innovations with firm growth, active resource reallocation, and economic prosperity.

2004), and the obsolescence process is assumed to be constant and homogeneous. Garcia-Macia, Hsieh, and Klenow (2019) highlight that technological obsolescence and destruction can originate from various sources, such as industry competitors' innovations, firms' own product improvements, and new varieties. This complexity makes the impact of obsolescence on firms, and its relative importance compared to the arrival of new innovations within a firm, unclear.

This paper starts from building *Technological Obsolescence* (*Obsolescence* for short) for public US firms that filed patents using the United States Patent and Trademark Office (USPTO) patent data from 1976 to 2020. The measure construction takes three steps. 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 in its existing patent portfolio. 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 firm-level measure can be viewed as an average level of obsolescence experienced by each specific technology in a firm's existing patent portfolio. The construction 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. The obsolescence measure will be $+10\%$ (comparing 900 with 1,000). 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.[2]

[2] Our measure will also capture cases in which a firm's technology base receive more citations over time. Say in the example, the firm's base received 1,100 citations in 2015. This will appear as -10% in obsolescence (comparing 1,100 with 1,000). Negative obsolescence, which happens more rarely, is a sign of staying at or approaching the frontier.

We conduct several analyses to show that our measure, as intended, effectively captures unique information on the destruction process of existing technologies. First, we compare our *Obsolescence* measure with various measures of new corporate innovations, including KPSS, Bellstam, Bhagat, and Cookson (2020), Kelly et al. (2021), Bowen III, Frésard, and Hoberg (2023). Our measure negatively correlates with all the new-innovation measures. The correlations have relatively low magnitudes compared to the positive correlations observed among these new-innovation measures themselves, suggesting that the *Obsolescence* measure captures independent information beyond new innovation. This desirable property originates from the fact that our measure builds upon only a firm's past innovation. Second, we show that the main variations in *Obsolscence* are from patents in the technology base that experience declines in citations, i.e., the base that is becoming obsolete. Last, we validate the measure using illustrative examples. For example, we leverage prior research on the Hard Disk Drive (HDD) industry (Christensen, 1997; Igami, 2017) to show that our measure closely captures the evolutionary process of technological obsolescence as old HDD technologies are replaced by new ones. In another example, we document that arrivals of radical innovation, as defined in Kelly et al. (2021), are followed by the technological obsolescence of disrupted firms and industries.

Armed with the measure, we first provide a comprehensive analysis of the level and cross-firm variations of technological obsolescence in corporate innovation, as well as its sources. Our measure indicates that a firm's patent portfolio experiences an average obsolescence rate of 4–7 percent annually. This average obsolescence rate is consistent with the estimates on the aggregate depreciation rate of patent value (see de Rassenfosse and Jaffe (2018) for a recent example).

The *Obsolescence* measure captures 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 suffering from 7–16 percent technology disruption annually. More than 60 percent of the variations is within-industry-year, across firms in the same SIC3 industry and year. The measure also captures various sources of technology disruption. Garcia-Macia, Hsieh, and Klenow (2019) point out that technological obsolescence could be due to within-firm innovation that cannibalizes a firm's own technology, industry competitors' technological breakthroughs, or disruptive innovation from outside the industry. We show empirically that these three sources are all significant in explaining variations in our technological obsolescence measure.

Next, we examine the relation between technological obsolescence and firm growth, productivity, and resource reallocation. 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 (2.9 percentage points), output (3.1 percentage points), capital (5.1 percentage points), and employment (1.8 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.

We show that this result is driven by the obsolescence of a firm's existing technologies, rather than the (lack of) arrival of new innovations. The results hold strongly when we only focus on patents in a firm that experience significant obsolescence, or only firms with positive *Obsolescence* values (i.e., loss of technological value). In addition, 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. Our findings are also robust to a broad set of measurement refinements and robustness checks, where we use various methods to correct the secular trend in patenting activities in the USPTO data, and explicitly account for patent aging and expiration.

The relationship 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 impacts 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), 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.

We also refine the measure to account for potential endogeneities of technological obsolescence, even though the original measure already considers only patents and citation counts that are not a function of firms' own innovation activities. Nevertheless, we find robust results when we construct the technology base using only patents that are more scientific and less firm-specific (general-purpose technologies, university patents, international patents etc.), such that the obsolescence is driven by scientific discoveries and advancements that are less contaminated by a firm's own recent past operations and performance.

In the last part of the paper, we ask: 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 ($t = 3.851$) monthly, or 7.1 percent per year, in a model with the Fama and French (2015) five factors 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 fail to fully incorporate 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, 2023).

In sum, this paper constructs a measure of technological obsolescence and demonstrates its value by applying it to three key questions in the literature on innovation and its intersection with financial economics. We hope that our analyses will serve as a foundation for future research to explore and revisit a range of fascinating questions related to corporate innovation using our measure.

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, 2023) 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, 2018; Li and Hall, 2020; Ewens, Peters, and Wang, 2024) 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. Note that the average obsolescence rate in this paper is lower than the average depreciation rates on accumulated R&D expenditures, which is often assumed to be around 15%. The difference stems from the fact that accumulated R&D expenditures incorporate knowledge capital from not only successful, but also failed innovation effort, which naturally depreciates faster.

This paper complements work that investigates the source of creative destruction and quantifies 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 the 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. 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, 2022; 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 that novelty often comes from the "decline" stage (Hoberg and Maksimovic, 2022). This paper contributes to this effort by continuously tracking the technological cycle a firms experience. We also provide the first evidence of financial market performance in response to this evolutionary process.

1. Technological Obsolescence: Data and Measurement

This section starts by briefly 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). The database provides detailed patent-level records on nearly seven million patents granted by the USPTO between 1976 and 2020.[3] 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.[4] 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

[3]We obtain the patent data from the USPTO PatentsView platform, accessible at https://www.patentsview.org/download/. USPTO official data start from 1976, the year when USPTO started the electronic filing that ensured systemic recording of citation information.

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

applications that had not yet been granted by the time of sample construction (Lerner and Seru, 2022).

Central to our analysis, for each patent p, we observe all the citations it makes to prior patents. 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 15 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.[5]

1.2. Measuring Technology Obsolescence

1.2.1. Conceptual Motivation. The aim of measuring a firm's technological obsolescence is to quantify the degree to which its existing technological portfolio (i.e., the stock of innovation) moves away from the technological frontier. This is distinct from measures of new innovations, which are widely used in the literature, that focus on capturing the arrival of new flows of innovation in a firm. To illustrate this point, consider Figure 1. In the left panel, firms have an existing portfolio of patents, each of which is represented by a navy ball. As time goes by, the firm experiences two things: (1) the obsolescence of the existing portfolio, as represented by the navy balls fading into different shades of light blue; and (2) the arrival of new innovation, as represented by the new red balls. Although the process of obsolescence of the whole patent portfolio and the process of new patents arriving are correlated, they are also quite independent, as we will demonstrate later.

From the micro perspective, technological obsolescence occurs at the level of a specific technology or patent, represented by the dots in Figure 1. Since most of our analyses, as well as those in the financial economics literature, are at the firm level, the construction of our measure focuses on the firm-level measure. This firm-level measure can be viewed as an average of the patent-level obsolescence measures, capturing the extent to which a firm's patent portfolio remains at the technology frontier.

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

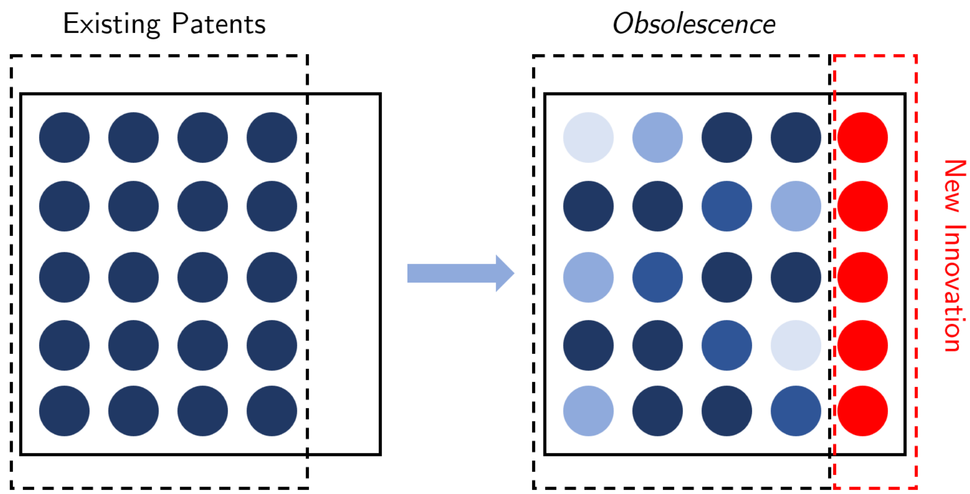


Figure 1. Illustration of Existing Patent Portfolio, Obsolescence, and Innovation

1.2.2. Construction. 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. This measure is constructed in three steps.[6]

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 is 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.[7]

Two empirical properties of the technology base of each firm are worth noting. First, by the nature of its construction, the base shows strong persistence. We find that the expansion rate

[6] In Online Appendix A.2, we provide a discussion on the mathematical formulation of the measure using citation matrices.

[7] When constructing the base, patent ownerships adjust for M&A activities and patent transactions as identified using SDC Platinum, PitchBook, and USPTO Patent Assignment Data, following the algorithm developed in Brav et al. (2018) and Ma, Tong, and Wang (2022).

of a firm's technology base is slow, roughly ten percent per year.[8] This is a desired property for our measurement construction requiring a stable proxy for the fundamental technologies that support each firm. 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 union of the two bases. More than 90% of the pairs have an overlap ratio of zero. This suggests that even firms in the same narrowly defined industry could be exposed to different future innovation disruptions because they used different technologies in their existing patent portfolios.

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 a subscript indicating the year the citation is calculated. We only track citations made by firms other than f itself in the $Cit(\cdot)$ operator. 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, or management decisions).

The number of citations received by each patent in each year reflects the usefulness of the patent in helping generate 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.[9] Figure 2 presents the age pattern of backward citations made by each new patent. This graph demonstrates the existence of technological obsolescence and the ability of citation data to capture such dynamics. New patents most likely build on patents that are aged 4 to 10 years, and they are less likely to cite patents from too far into the past. This is consistent with older innovations losing value and relevance as technology evolves.[10]

[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.

[9] The method draws inspiration from the literature of bibliometrics and scientometrics that measures the obsolescence and aging of a scientific discipline. The diachronous approach in these strands of literature uses over-time changes in citations made to the set of technologies (the technology base in our paper) to capture the dynamic relevance of the underlying technologies (Cunningham and Bocock, 1995; Sun, Min, and Li, 2016).

[10] In Appendix A.1 we provide an extensive discussion on patterns of citation dynamics of patents.

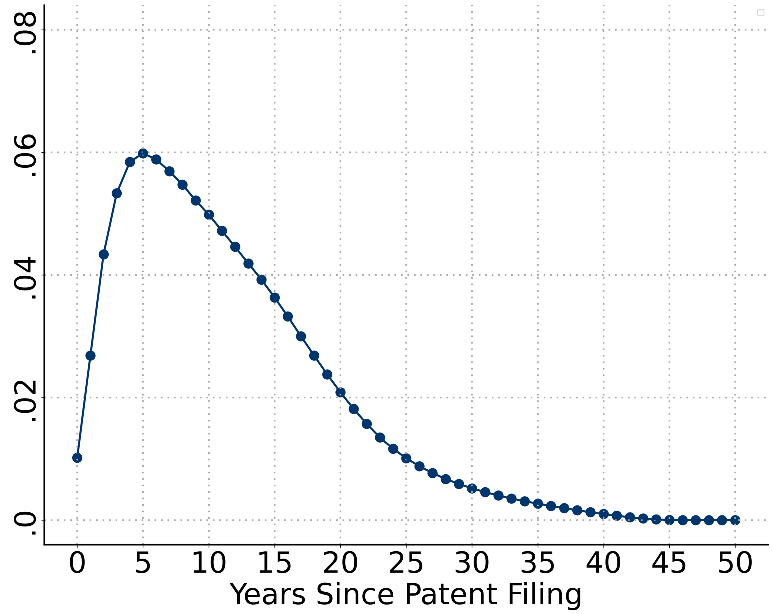


Figure 2. Patent Backward Citation Dynamics

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.

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 the effects of firm size and the size of knowledge space, and it mitigates systematic differences of citation norms across different sectors.

1.2.3. Discussions on The Construction. The *Obsolescence* construction above will be used as the main measure. However, several steps in the construction process could lead to different variations of the measure, and we review them below. These choices will later be empirically examined later to show the robustness of our main findings.

First, does *Obsolescence* really capture the obsolescence part of a firm's portfolio? The method can be modified to calculate the *Obsolescence* of certain subsets of the patent portfolio. In particular, we can construct *Obsolescence* using only the subset of patents in the base that experience citation declines during $t-\omega$ and t. In this way, the measure can more explicitly capture variations driven by the set of technologies that are quickly getting outdated.

Next, it is useful to acknowledge there is a long-term secular increase in the number of patents during our sample period. As a result, patents could be cited more as time goes by due to the higher patenting intensity, which may impact the specific magnitude of *Obsolescence*. We explore a time-trend-adjusted obsolescence measure. The logic is that we follow Kaltenberg, Jaffe, and Lachman (2023) and adjust any citation in a year to be the same as the patent-per-capita number as in 1980. In this way, the adjustment will erase the trend in citation counts.

Additionally, this $Cit(\cdot)$ operator underweights the impact of outdated and less relevant patents in the base, as the citations they receive would weight less in the total citations received by a base. We also show the robustness by explicitly adjusting the weight of citations made to different vintages of patents in a technology base, such as excluding citations made to expired patents, and an adjustment using a depreciation rate.

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 2.6, these different versions of the measure will be used to further isolate variations to technological obsolescence independent of firm operations.

1.2.4. Alternative Construction. The economic logic behind the *Obsolescence* construction is to track citation movements around a firm's technology stock. Through this construction, *Obsolescence* proxies for variations in the value and usefulness of the technology base of each firm. Following Newton's metaphor, when a firm is already on the shoulder of a standing Giant, the *Obsolescence* measure captures variations in the height of the Giant (e.g., making the Giant sit or jump). Our main construction relies on non-self citations made to the technology base of a firm after excluding the firm's own patents from this base.

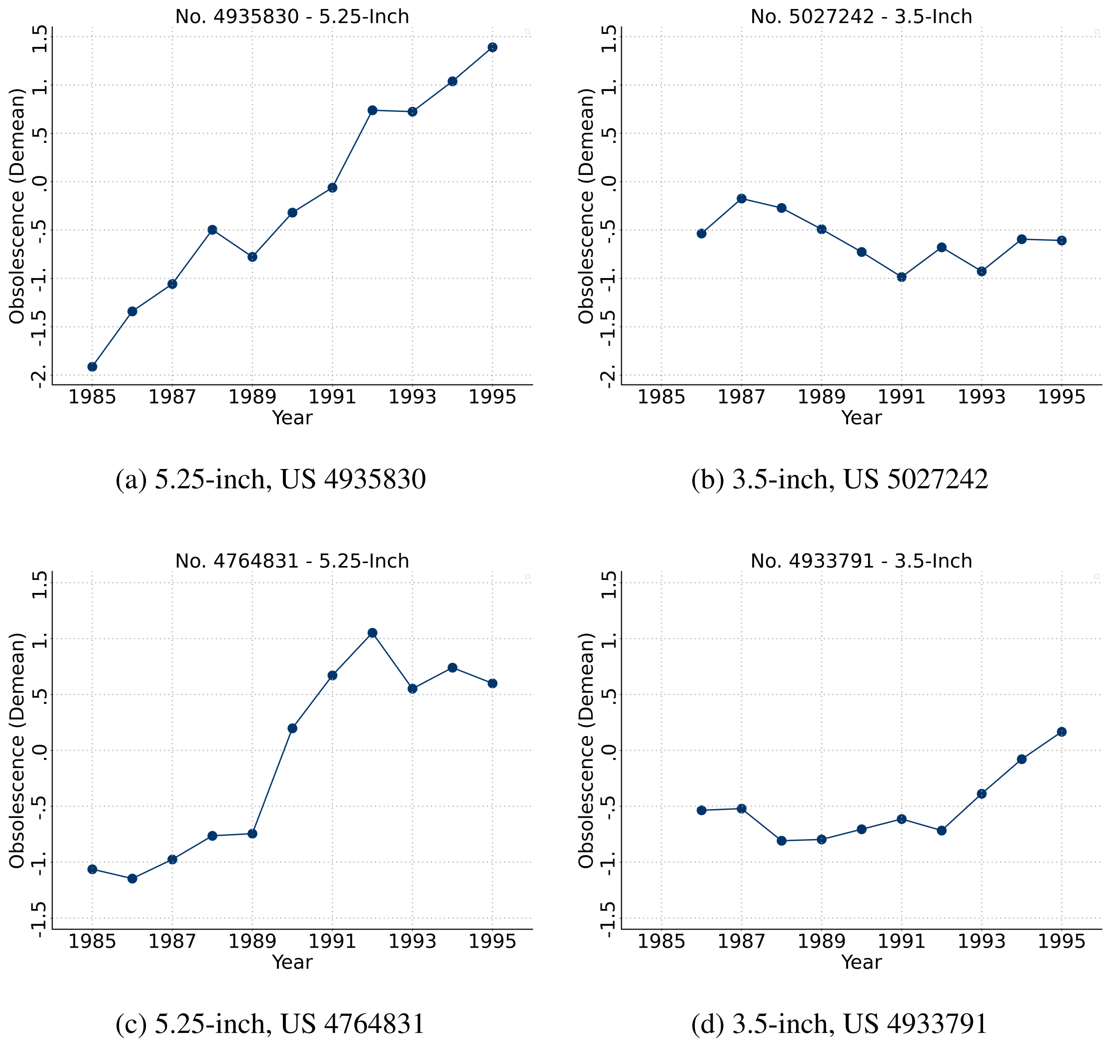
In Section 2.7, we discuss and provide empirical analysis for a natural alternative candidate to measure obsolescence: the changes in annual citations made to firm f's *own* patents, instead of those to the technology base. For example, if f's own patent portfolio receives 100 citations in 2000 and only 50 in 2005, that is a reasonable sign of f moving away from the technology frontier.

This alternative construction is arguably more direct in capturing the decline in the relevance of a firm's patent portfolio. However, there are a few important motivations behind the choice of focusing on the main construction outlined in Section 1.2.2 and tracking citations to technology bases. First, technology bases usually include a larger set of patents, and thus experience less noisy bumpiness in citation dynamics, especially for firms with smaller patent portfolios. Second, using the technology base excluding a firm's own patents allows the variations to be more arms-length from the firm's own operations—a desirable empirical property for many research designs. In Section 2.7, we provide empirical evidence on the properties of the two measures that support our choice and discuss how these measures can be useful for future research with various focuses.

1.3. Illustrative Examples

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.[11] 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).

[11] 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.*



(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 3. 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.

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.

We show two pairs of patents, corresponding to two different types of core technologies associated with building HDDs.[12] The first pair of patents are general-design patents of HDD. For

[12]For readers interested in learning more about HDD patents, we hereby describe the procedure used in building the

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 3, 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 *Obsolescence* in affected firms after those breakthrough innovations.

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 4 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.

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 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.

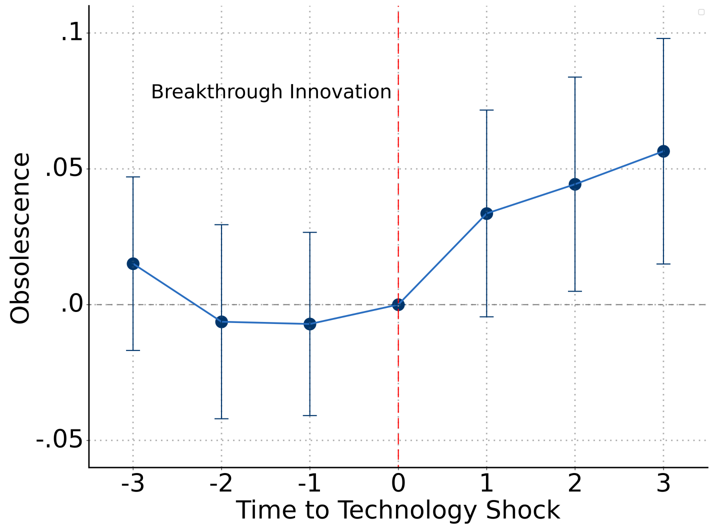


Figure 4. *Obsolescence* In Response to Breakthrough Innovation

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.

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 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 the filing year and the 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 whose technologies are better positioned to remain at the frontier have a low obsolescence rate 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 A.1, 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).

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 paper books).

[Insert Table 2 Here.]

Table 2 presents a simple analysis that projects *Technological Obsolescence* on three dimensions of 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).

1.5. Relations with Measures of New Innovations

We also provide analyses to compare our *Obsolescence* with several leading measures of new innovation in a firm. These analyses serve two purposes before performing empirical exercises using *Obsolescence*. First, these analyses can help us assess whether our new measure captures unique variations in the multi-dimensional complex innovation space. Second, these analyses will motivate several key control variables that will be used in later analysis.

[Insert Table 3 Here.]

Table 3 panel (a) summarizes several leading firm-year level measures of new innovations: Patent Value (SM) is the stock market-based patent value from Kogan et al. (2017); Citation-Weighted Patents (CW) is the citation-weight patent counts, which has a long intellectual history, and we follow Kogan et al. (2017) for construction; % Breakthrough Patents is the share of breakthrough patents of firms' patents in that year, in which the definition of breakthrough patents is from Kelly et al. (2021); RETech measures whether the patent pertains to a technological area that is rapidly evolving (i.e., following breakthroughs) or stable from Bowen III, Frésard, and Hoberg (2023); Tech Breadth measures how much (or little) the patent's text is spread across technological fields from Bowen III, Frésard, and Hoberg (2023); Text-Based Innovation is the text-based innovation measure from Bellstam, Bhagat, and Cookson (2020).

Conceptually, a key difference between these measures of new innovation and *Obsolescence* is reflected in Figure 1. *Obsolescence* intends to capture features of existing patents stock up to a certain time, while the new innovation measures intend to capture the quantity and quality of the flow of innovation.

Empirically, the correlation structure of these new innovation measures and *Obsolescence* is presented in panel (b) of Table 3. There are two takeaways. First, *Obsolescence* consistently has negative correlations with the new innovation measures, indicating that *Obsolescence* is capturing variations on the "negative" side in the innovation space. The correlations are generally mild in terms of magnitude, suggesting that *Obsolescence* captures useful and independent sources of information in a firm's innovation portfolio. Second, the correlations among the innovation measures themselves are all positive, which is reassuring. The correlations tend to be mild in magnitude but higher than the correlations with *Obsolescence*, reflecting the fact that these measures are usually constructed using different sets of information from patents and aimed at capturing different dimensions of new innovation.

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, as well as the 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 the ω parameter is omitted in this and later equations. 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 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 1 panel (b) provides summary statistics at the firm-year level.

In all our analyses, we include SIC3-by-year fixed effects to account for unobserved factors at the industry-year level. All the results are estimated by 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 4. For each outcome variable, we keep the sample as all the observations with non-missing values from $t+1$ to $t+5$; and this also explains the slightly different numbers of observations across outcome variables. Our results are not sensitive to any of these choices: see Appendix Table A.2 for results when the non-missing value condition is not enforced; results with other obsolescence horizon parameters $\omega = 1, 3$ are presented in Appendix Table A.3 and Table A.4.

We see negative estimates of βs across the growth rate of profits, output, capital, and employees. One standard deviation higher in obsolescence is associated with lower profits and lower output of 2.9 and 3.1 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 5.1 percent during the same five-year period, and total employment decreases by 1.8 percent. We find that 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 4 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 5.[13]

[13] In Appendix Table A.17, we perform analyses controlling for alternative measures of new innovation that are discussed in Section 1.5. Our results are robust when including these controls.

[Insert Table 5 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 5 with those in Table 4, 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 climb up with the help of new innovation, while obsolete incumbents remain in the industry for a long time.[14]

[Insert Table 6 Here.]

In addition, we isolate the true obsolescence part of the variation in *Obsolescence*, and show that the results are mainly driven by this part in the *Obsolescence* measure. Specifically, we reconstruct the *Obsolescence* measure with one modification: instead of using all patents in a firm's technology base to track changes in citations between $t-\tau$ and t, we use only patents in the base that experienced a decline of citations over this time window. This approach isolates variations in *Obsolescence* driven by patents losing value, and it does not mix these patents with those that are

[14] This is also consistent with our findings when exploring extreme outcomes such as bankruptcy, presented in Appendix Table A.5. We found a mild and statistically noisy effect of obsolescence leading to bankruptcy in the next five years.

gaining value.[15] In Table 6, we present results that are similarly formatted to those in Table 5, but using this new construction of *Obsolescence*. We find that the results hold strongly statistically and with comparable economic magnitudes across different outcome variables and time horizons. In Table A.6, we construct another version of *Obsolescence* that isolates only the variations from the citation-declining patents. Specifically, we truncate citations to patents in the technology base at zero, replacing those with positive citation growth with zero growth. The results are again similar qualitatively and quantitatively.

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.

[15] Percentages of patents with increases in citations, decreases in citations, and no changes in citations are 20.4%, 64.5%, and 15.1%, respectively. This means, reassuringly, that the majority of the patents in the knowledge base experience some level of obsolescence and thus are used in the construction of this construction.

2.3. Heterogeneity: Innovation Types and Market Competition

In Table 7 we present several key heterogeneity analyses.[16] 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 (2022) 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 based on whether the patent category belongs to the main categories of the firm, defined as those top patent categories that include 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 a 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

[16] Appendix Table A.7 presents heterogeneity analysis with alternative control variables.

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 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 3.8 percent decrease of capital stock and a 1.7 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 disrupts 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 the homogeneous relevance of industry competitors. This assumption can be very strong given what we document above in Figure A.7 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, 2022). (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.[17] Moreover, in most of the analysis, 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. Robustness of the Results

We conduct a set of additional analyses to examine the robustness and uniqueness of the *Obsolescence* measure. These analyses echo Section 1.2, which discusses several alternative measurement construction choices.

In Tables A.8 and A.9 in the Appendix, we explicitly consider the depreciation of a patent's relevance in the technology base, with the idea that some very old patents should be less relevant when measuring a firm's technological dynamics. Two approaches are adopted: excluding patents from the technology base after they expire (20 years in the US), or using a constant annual discount rate of 0.9 to discount citations received by patents in the base. The results hold strongly.

Next, in Table A.10, we perform an analysis to adjust for the secular trend in patenting activities reflected in the USPTO data. This secular change, put simply, is the trend that more and more patents are being filed to the USPTO, and as a result, patents could be cited more over time due to the higher patenting intensity. Given our calculation in equation (1) that relies on citation dynamics,

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

it is important to understand the impact of the trend. We produce a time-trend-adjusted obsolescence measure. The logic is that we follow Kaltenberg, Jaffe, and Lachman (2023) and adjust any citation in a year to be the same as the patent-per-capita number as in 1980. In this way, the adjustment will deflate the secular increase of citations. Table A.10 shows that this issue does not affect our main result, which primarily rests on cross-sectional variations.

Even though the *Obsolescence* measure is best positioned to study the cross-sectional variations within the same industry, we also explore the robustness of our results to the inclusion of firm-level fixed effects. In Table A.11, we show that the results are robust to this inclusion.

2.6. 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 2.7, we mitigate the influence of a firm's own decisions by excluding the firm's own patents from the technology base and 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 is mitigated. Similarly, in Appendix Table A.12, we reproduce our results excluding the focal firm's market competitors from the construction of the technology base and citation dynamics. One version defines market competitors using 3-digit SIC industry classification, and the other uses the definition from Hoberg-Phillips's text-based categorization (Hoberg and Phillips, 2016). The results are robust to this construction.

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 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.13 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.14 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).

2.7. Alternative Construction

An alternative candidate to measure obsolescence is the change 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 correlation between this alternative measure and the primary technological obsolescence measure is 0.361. In the Appendix Table A.15, we show that this alternative measure yields even stronger results in all our analyses.

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. Two main reasons motivate us to use the current construction: the ability to smoothly track technological evolution, and the ability to (partially) address the endogeneity problem when conducting firm-level studies.

First, the technology bases of firms, as in our measure construction, are usually much broader than the set of patents a firm owns. As a result, citations made to this broader set of technologies are less bumpy over the years, while the citations made to the smaller set of a firm's own patents could be volatile. In our sample, a firm's own patent portfolio on average consists of about 40 patents at each point in time, while a firm's technology base consists of on average 600 patents. This translates to a smoother variable that can better capture the true fundamentals of technology movement.

Second, the primary *Obsolescence* measure in the paper, based on the technology base, is more arms-length from a firm, and thus potentially more immune to the endogeneity problem when conducting firm-level studies. It also offers us more flexibility in addressing them further. For example, one could sensibly worry that if we capture the decline of citations to a firm's own patents as in the alternative measure, it could be attributed to the firm experiencing non-technology-based shocks (such as a cash flow shock, financing shock, management change, etc.) that could affect other firms' willingness to follow their technologies and future firm performance at the same time. Tracking patents in the base can partially circumvent this issue.

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 the 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.18 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). In addition, we 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.

It is worth noting that our sample consists of firms that are innovative and frequently patent. When pricing the portfolios using these traditional asset pricing models, we find that our sample has a significant, positive, and sizable alpha. Specifically, row "all" shows that the alphas are overwhelmingly positive and significant, meaning that stocks in our sample have on average outperformed the overall market. This sample-specific level effect makes it challenging to properly interpret the level of the alpha associated with returns of the *Obsolescence*-sorted portfolios without adjustment, as those in panel (a).

To adjust for this sample-specific level affect, in panel (b), we include a sample-specific market factor in the regressions, i.e., the value-weighted average of the returns of all stocks in our sample. This factor will naturally mitigate the sample-specific mispricing, making the levels of alphas more interpretable, while having little impact on the long-short portfolio results. Intuitively, this is similar to adjusting for a sample-specific fixed effect against the full sample of public firms. After performing this correction, we find consistent negative alphas associated with the high-*Obsolescence* portfolio, and consistent positive alphas associated with the low-*Obsolescence* portfolio. For instance, in the four-factor model, the low-*Obsolescence* portfolio has an alpha of 0.27% per month, while the high-*Obsolescence* portfolio has an alpha of -0.17% per month, both statistically significant.

In the Online Appendix, we provide a battery of robustness checks and additional results. The findings hold true for equal-weight portfolios as reported in Table A.19. 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.20. 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.21. The effect is also robust when we perform the portfolio sorting using by-industry breakpoints each year or the industry-year-demeaned *Obsolescence* measure, shown in Table A.22. In Appendix Table A.23, 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) of Table 9, 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.24.

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).[18]

We test whether investors form incorrect expectations about the future profitability of firms with 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., 2024).

[18] 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).

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 follows Bouchaud et al. (2019) and 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.[19]

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 the innovation productivity of the economy.

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 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

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

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 direction is to use the *Obsolescence* measure to examine more questions in corporate finance, innovation economics, and industrial organization. This paper devotes a large part of the effort to establish the measure's intuition and validity. However, the measure can be used to examine a wide range of questions—at the level of inventors, firms, or a certain industry.

For example, one can 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 on this topic. The question would be more interesting after taking into account the fact, as documented in the paper, investors do not fully incorporate technology into allocating resources.

The *Obsolescence* measure, while presented here at the firm-year level to facilitate connections with firm-level and financial market studies, has broader applications beyond this scope. The underlying methodology can be adapted to measure obsolescence across multiple domains: individual technologies, technology clusters, inventors' and scientists' human capital, or the aggregate knowledge capital of regions and countries. While detailed analyses at these levels exceed the boundaries of this study, such applications offer promising avenues for future research across various fields.

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.

Code Availability: The replication code and data are available in the Harvard Dataverse at https://doi.org/10.7910/DVN/Y9M30R.

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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Table 1. Firm-Year Level Summary Statistics

	count	mean	std	10%	25%	50%	75%	90%
Panel (a): *Innovation Measures*								
Obsolescence, Horizon $\omega = 1$ (%)	32,697	7.843	13.384	-8.039	-0.414	7.438	15.667	24.202
Obsolescence, Horizon $\omega = 3$ (%)	32,697	12.900	26.557	-19.869	-3.336	13.346	29.456	44.768
Obsolescence, Horizon $\omega = 5$ (%)	32,697	19.390	34.965	-22.926	-1.626	19.065	40.465	62.389
Obsolescence, Horizon $\omega = 10$ (%)	30,644	34.126	51.844	-28.776	0.867	32.694	65.797	100.861
Stock Market-Based Patent Value (SM) (%)	32,697	15.322	33.402	0.000	0.251	3.699	15.612	41.504
Citation-Weighted Patents (CW) (%)	32,697	7.788	20.317	0.000	0.095	1.484	5.926	17.739
Competitors' Patent Value (%)	32,697	25.022	32.516	0.455	4.803	17.398	30.553	50.144
Competitors' Citation-Weighted Patents (%)	32,697	2.880	2.698	0.075	0.687	1.853	4.594	7.073
Panel (b): *Firm Performance and Characteristics*								
Profits, Growth Rate (%)	29,734	4.132	29.619	-24.289	-6.369	4.575	15.529	32.283
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	-8.381	0.140	5.520	12.548	23.870
Labor, Growth Rate (%)	31,654	2.021	21.017	-16.705	-5.215	1.660	9.673	22.314
TFP, Growth Rate (%)	23,816	-0.810	25.809	-24.325	-9.867	-0.415	9.179	22.837
Profits	32,689	2,190.551	5,878.533	7.210	48.198	260.424	1,269.023	5,202.854
Output	32,290	6,285.039	16,637.534	27.621	132.299	723.575	3,760.237	15,724.789
Capital	32,596	4,388.214	15,874.031	11.279	44.204	259.103	1,774.694	8,185.960
Labor	32,342	17.702	41.084	0.133	0.520	2.866	13.500	47.314
TFP	25,055	-0.336	0.448	-0.798	-0.539	-0.332	-0.113	0.166
Patent Stock	32,697	599.323	1,998.837	15	25	59	243	1,165
Firm Age	32,697	28.374	15.646	11	16	25	38	49
Idiosyncratic Volatility	32,623	0.001	0.002	0.000	0.000	0.001	0.001	0.003

Notes. This table summarizes firm-year level 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. 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); TFP is revenue-based productivity constructed based on the methodology of Olley and Pakes (1996) using the procedure in İmrohoroğlu and Tüzel (2014); 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 starting from the time that the investor filed its first patent application or entered the Compustat. Idiosyncratic Volatility is the realized mean idiosyncratic squared returns, where the 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 2. Sources of Technological Obsolescence

	(1)	(2)	(3)	(4)
	Obsolescence			
Firm's Own New Patent Value	0.052***	0.079***	0.072***	0.104***
	(0.011)	(0.015)	(0.014)	(0.020)
Competitors' Patent Value	0.050**	0.042	-0.004	0.018
	(0.022)	(0.025)	(0.044)	(0.035)
Upstream Effects of Innovation	0.041	0.057**		
	(0.026)	(0.027)		
Economy-Wide Index of Innovation			0.108**	0.098**
			(0.052)	(0.037)
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	No	No
Observations	27,671	27,671	28,049	28,049
R^2	0.271	0.505	0.132	0.408

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. Control variables include the log value of average total assets in the past five years, the log value of the average book-to-market ratios in the past five years, and the average value of the firm's idiosyncratic volatility in the past five years. 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 3. Relations Between *Obsolescence* and Measures of New Innovation

Panel (a): A List of Measures of New Innovation

	Main Reference	Sample Period	Firm Sample	Patent Sample
Patent Value (SM) Citation-Weighted Patents (CW)	Kogan et al. (2017) (KPSS)	1926-2020	All US public firms	All patents from US public firms
% Breakthrough Patents	Kelly et al. (2021) (KPST)	1840-2002	N/A	All patents
RETech Tech Breadth	Bowen III, Frésard, and Hoberg (2023) (BFH)	1910-2017	VC-backed US startups	All patents
Text-Based Innovation	Bellstam, Bhagat, and Cookson (2020) (BBC)	1989-2010	All S&P 500 firms	All patents from S&P 500 firms

Panel (b): Correlation Between *Obsolescence* and Innovation Measures

	Obsolescence	Patent Value (SM)	Citation-Weighted Patents (CW)	% Breakthrough Patents	RETech	Tech Breadth	Text-Based Innovation
Obsolescence	1	-0.061	-0.085	-0.148	-0.105	-0.005	-0.083
Patent Value (SM)	-0.061	1	0.307	0.157	0.243	-0.152	0.378
Citation-Weighted Patents (CW)	-0.085	0.307	1	0.151	0.101	-0.009	0.2
% Breakthrough Patents	-0.148	0.157	0.151	1	0.373	-0.21	0.426
RETech	-0.105	0.243	0.101	0.373	1	-0.413	0.227
Tech Breadth	-0.005	-0.152	-0.009	-0.21	-0.413	1	-0.303
Text-Based Innovation	-0.083	0.378	0.2	0.426	0.227	-0.303	1

Notes. This table examines the correlation between *Obsolescence* and other innovation measures: Patent Number is the number of patents that the firm files in that year; Avg. Citation Per Patent is the average citations of those patents in that year; Patent Value (SM) is the stock market-based patent value from Kogan et al. (2017); Citation-Weighted Patents (CW) is the citation-weighted patent counts following Kogan et al. (2017); % Breakthrough Patents is the share of breakthrough patents of firms' patents in that year and the definition of breakthrough patents is from Kelly et al. (2021); RETech measures whether the patent pertains to a technological area that is rapidly evolving (i.e., following breakthroughs) or stable from Bowen III, Frésard, and Hoberg (2023); Tech Breadth measures how much (or little) the patent's text is spread across technological fields from Bowen III, Frésard, and Hoberg (2023); Text-Based Innovation and Neg. Text-Based Innovation is the text-based innovation measure and negative text-based innovation measure from Bellstam, Bhagat, and Cookson (2020). For each measure pair, we use the overlap firm-year observations to calculate the correlation.

Table 4. Technological Obsolescence and Firm Growth

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.013***	-0.021***	-0.025***	-0.029***	-0.029**
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
R^2	0.251	0.269	0.268	0.260	0.252
			Output (N =22,358)		
$Obsolescence_t$	-0.009**	-0.017***	-0.022***	-0.027**	-0.031**
	(0.004)	(0.006)	(0.008)	(0.010)	(0.013)
R^2	0.201	0.211	0.211	0.208	0.208
			Capital (N =22,873)		
$Obsolescence_t$	-0.013***	-0.024***	-0.034***	-0.044***	-0.051***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
R^2	0.178	0.196	0.202	0.202	0.198
			Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.012**	-0.016**	-0.018**	-0.018*
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
R^2	0.170	0.179	0.182	0.181	0.181
			TFP (N =16,639)		
$Obsolescence_t$	-0.007*	-0.010**	-0.013**	-0.016***	-0.014**
	(0.003)	(0.005)	(0.005)	(0.005)	(0.006)
R^2	0.236	0.293	0.327	0.341	0.344

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 1. 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 5. Technological Obsolescence and Growth, Controlling For Innovation Measures

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.012***	-0.019***	-0.022***	-0.025***	-0.025**
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	0.002	0.005	0.009	0.007	0.011
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.026**	0.035**	0.045**	0.055***
	(0.007)	(0.011)	(0.014)	(0.017)	(0.018)
R^2	0.254	0.272	0.272	0.265	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.008**	-0.016**	-0.021**	-0.024**	-0.028**
	(0.004)	(0.006)	(0.008)	(0.010)	(0.013)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.005	-0.007	-0.008	-0.007
	(0.004)	(0.007)	(0.010)	(0.012)	(0.015)
Patent Value$_t$ (SM)	0.014**	0.021*	0.029**	0.035*	0.046**
	(0.006)	(0.011)	(0.014)	(0.019)	(0.020)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.013***	-0.022***	-0.032***	-0.041***	-0.048***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.013***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.028***	0.036***	0.042**	0.049**
	(0.004)	(0.008)	(0.012)	(0.016)	(0.018)
R^2	0.185	0.203	0.208	0.207	0.204
			Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.011**	-0.015**	-0.016*	-0.017
	(0.002)	(0.005)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.007	-0.008	-0.010	-0.014
	(0.003)	(0.005)	(0.007)	(0.010)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.028**	0.033**
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.006*	-0.008*	-0.011**	-0.014***	-0.012*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0.000	0.006	0.008	0.005	0.006
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.024*	0.030**	0.033***
	(0.009)	(0.012)	(0.012)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

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-weighted patent counts. The design follows that in Table 4.

Table 6. Technological Obsolescence and Growth, Isolating Variations in *Obsolescence*

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.016***	-0.025***	-0.029***	-0.032***	-0.033***
	(0.003)	(0.005)	(0.007)	(0.008)	(0.009)
Citation-Weighted Patents$_t$ (CW)	0.001	0.003	0.006	0.005	0.008
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.015**	0.024**	0.033**	0.043**	0.052***
	(0.007)	(0.011)	(0.013)	(0.016)	(0.018)
R^2	0.255	0.273	0.273	0.266	0.259
			Output (N =22,358)		
$Obsolescence_t$	-0.010***	-0.021***	-0.025***	-0.030***	-0.037***
	(0.004)	(0.005)	(0.007)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.006	-0.007	-0.009	-0.010	-0.010
	(0.004)	(0.007)	(0.010)	(0.012)	(0.015)
Patent Value$_t$ (SM)	0.013**	0.020*	0.027*	0.033*	0.043**
	(0.005)	(0.010)	(0.013)	(0.019)	(0.019)
R^2	0.203	0.213	0.214	0.211	0.213
			Capital (N =22,873)		
$Obsolescence_t$	-0.016***	-0.028***	-0.041***	-0.053***	-0.063***
	(0.002)	(0.004)	(0.007)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	-0.011***	-0.014***	-0.017**	-0.017*	-0.018*
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.015***	0.026***	0.033***	0.037**	0.044**
	(0.004)	(0.008)	(0.011)	(0.015)	(0.017)
R^2	0.187	0.205	0.211	0.211	0.208
			Labor (N =23,511)		
$Obsolescence_t$	-0.008***	-0.014***	-0.020***	-0.022***	-0.027***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.006*	-0.008	-0.010	-0.011	-0.016
	(0.003)	(0.005)	(0.008)	(0.010)	(0.011)
Patent Value$_t$ (SM)	0.010***	0.017**	0.021**	0.026**	0.031**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.185	0.185
			TFP (N =16,639)		
$Obsolescence_t$	-0.008**	-0.012**	-0.012**	-0.013**	-0.011
	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
Citation-Weighted Patents$_t$ (CW)	-0.000	0.005	0.008	0.004	0.005
	(0.003)	(0.006)	(0.007)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.014	0.018	0.023*	0.029**	0.032***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity using a new construction. Specifically, this approach reconstructs the *Obsolescence* measure with one modification: instead of using all patents in a firm's technology base when tracking changes in citations between $t-\tau$ and t, we use only patents in the base that experienced a decline of citations over this time window. The table 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			
$Obsolescence_t$	-0.021***	-0.006	-0.025***	-0.010*	-0.024***	-0.026*
	(0.007)	(0.007)	(0.007)	(0.005)	(0.008)	(0.015)
R^2	0.267	0.266	0.268	0.267	0.242	0.383
Observations	21,274	21,274	21,274	21,274	15,513	5,761
			Output			
$Obsolescence_t$	-0.022***	-0.005	-0.022**	-0.008	-0.023**	-0.018
	(0.008)	(0.007)	(0.008)	(0.005)	(0.010)	(0.012)
R^2	0.211	0.210	0.211	0.210	0.189	0.348
Observations	22,358	22,358	22,358	22,358	16,564	5,794
			Capital			
$Obsolescence_t$	-0.030***	-0.014**	-0.034***	-0.011*	-0.038***	-0.014
	(0.007)	(0.006)	(0.008)	(0.006)	(0.009)	(0.010)
R^2	0.202	0.199	0.202	0.198	0.184	0.297
Observations	22,873	22,873	22,873	22,873	17,022	5,851
			Labor			
$Obsolescence_t$	-0.013**	-0.006	-0.018**	-0.006	-0.017**	-0.007
	(0.006)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
R^2	0.182	0.181	0.182	0.181	0.156	0.307
Observations	23,511	23,511	23,511	23,511	17,525	5,986
			TFP			
$Obsolescence_t$	-0.013***	-0.007	-0.013**	-0.008**	-0.014**	-0.007
	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.008)
R^2	0.327	0.327	0.327	0.327	0.302	0.474
Observations	16,639	16,639	16,639	16,639	12,804	3,835

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 4, 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 (N =21,274)		
$Obsolescence_t$	-0.012***	-0.020***	-0.023***	-0.026***	-0.026**
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$ (SM)	0.017**	0.027**	0.036**	0.045***	0.055***
	(0.007)	(0.011)	(0.013)	(0.016)	(0.018)
Competitors' Patent Value$_t$	-0.001	-0.011	-0.013**	-0.025***	-0.024**
	(0.005)	(0.007)	(0.006)	(0.008)	(0.009)
R^2	0.254	0.272	0.272	0.266	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.007**	-0.015**	-0.020**	-0.024**	-0.027**
	(0.004)	(0.006)	(0.008)	(0.010)	(0.013)
$Patent\ Value_t$ (SM)	0.013**	0.020**	0.028**	0.034*	0.045**
	(0.005)	(0.010)	(0.013)	(0.018)	(0.019)
Competitors' Patent Value$_t$	-0.003	-0.001	0.002	-0.005	-0.008
	(0.005)	(0.008)	(0.008)	(0.010)	(0.010)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.012***	-0.021***	-0.031***	-0.040***	-0.047***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
$Patent\ Value_t$ (SM)	0.014***	0.025***	0.033***	0.038**	0.046***
	(0.004)	(0.007)	(0.011)	(0.014)	(0.016)
Competitors' Patent Value$_t$	-0.010**	-0.011	-0.015	-0.019*	-0.019
	(0.004)	(0.008)	(0.009)	(0.011)	(0.012)
R^2	0.183	0.202	0.208	0.207	0.204
			Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.010**	-0.014*	-0.015*	-0.016
	(0.002)	(0.005)	(0.007)	(0.009)	(0.010)
$Patent\ Value_t$ (SM)	0.010***	0.016**	0.021**	0.026**	0.030**
	(0.003)	(0.006)	(0.008)	(0.011)	(0.013)
Competitors' Patent Value$_t$	0.000	-0.000	-0.001	-0.002	-0.004
	(0.004)	(0.007)	(0.008)	(0.008)	(0.009)
R^2	0.172	0.181	0.184	0.184	0.183
			TFP (N =16,639)		
$Obsolescence_t$	-0.006*	-0.008*	-0.012**	-0.014***	-0.012*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
$Patent\ Value_t$ (SM)	0.014	0.019	0.024**	0.031***	0.033***
	(0.009)	(0.013)	(0.012)	(0.011)	(0.010)
Competitors' Patent Value$_t$	-0.011	-0.017**	-0.000	0.004	-0.004
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
R^2	0.239	0.296	0.331	0.346	0.350

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 4.

Table 9. Monthly Returns of Obsolescence-Sorted Portfolios

Panel (a): Value-Weight Portfolio, with Factor Models

	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***
	(0.268)	(0.085)	(0.084)	(0.086)	(0.095)	(0.095)	(0.094)	(0.094)
Middle	0.639***	0.065	0.108	0.007	-0.100	0.040	0.078	0.028
	(0.239)	(0.066)	(0.067)	(0.067)	(0.080)	(0.069)	(0.073)	(0.068)
High	0.587**	-0.029	0.027	-0.157	-0.194*	-0.082	-0.024	-0.144
	(0.235)	(0.103)	(0.103)	(0.096)	(0.112)	(0.101)	(0.105)	(0.097)
Low–High	0.302*	0.418***	0.357**	0.570***	0.530***	0.505***	0.434***	0.588***
	(0.178)	(0.152)	(0.150)	(0.148)	(0.161)	(0.156)	(0.159)	(0.150)
All	0.706***	0.148***	0.173***	0.091**	0.007	0.134**	0.154***	0.114**
	(0.234)	(0.047)	(0.048)	(0.045)	(0.055)	(0.052)	(0.055)	(0.051)

Panel (b): Value-Weight Portfolio, with Factor Models and Sample-Specific Market Factor

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.889***	0.294***	0.270***	0.336***	0.330***	0.316***	0.284***	0.340***
	(0.268)	(0.087)	(0.084)	(0.086)	(0.095)	(0.091)	(0.089)	(0.088)
Middle	0.639***	-0.105***	-0.089**	-0.096**	-0.108**	-0.110***	-0.092**	-0.098**
	(0.239)	(0.040)	(0.039)	(0.039)	(0.046)	(0.041)	(0.039)	(0.040)
High	0.587**	-0.199**	-0.166**	-0.240***	-0.201**	-0.213***	-0.171**	-0.240***
	(0.235)	(0.080)	(0.080)	(0.078)	(0.083)	(0.082)	(0.082)	(0.077)
Low–High	0.302*	0.493***	0.436***	0.575***	0.531***	0.528***	0.454***	0.580***
	(0.178)	(0.149)	(0.146)	(0.145)	(0.159)	(0.157)	(0.155)	(0.147)

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)	(0.025)
Middle	0.969***	-0.132***	-0.068**	-0.055**
	(0.029)	(0.023)	(0.027)	(0.027)
High	0.942***	-0.031	0.153**	-0.073*
	(0.032)	(0.044)	(0.068)	(0.040)
Low–High	0.030	-0.022	-0.497***	0.079
	(0.041)	(0.064)	(0.087)	(0.058)
All	0.963***	-0.093***	-0.100***	-0.033*
	(0.020)	(0.016)	(0.021)	(0.018)

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. We also construct a portfolio containing all the stocks in our sample, labeled as All. 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. 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 panel (a) we report the results for value-weight portfolios. In panel (b) we include a sample-specific market factor in the regressions to correct for the sample-specific abnormal return. 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	-0.514**	-0.469**	-0.793**	-0.771**
	(0.216)	(0.212)	(0.339)	(0.347)
Observations	22,846	22,846	20,624	20,624
R^2	0.024	0.024	0.032	0.032
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 $\tau = 1,2$. In all columns, we control 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. Columns (2) and (4) have additional controls of new innovation measures, including the stock market-based patent value from Kogan et al. (2017), and citation-weighted patent counts. 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.

Internet Appendix for

Technological Obsolescence

SONG MA

* Citation format: Ma, Song, Internet Appendix for "Technological Obsolescence," *The Review of Financial Studies*, DOI: XXXXX. Any queries (other than missing materials) should be directed to Song Ma, Yale School of Management, 165 Whitney Ave, New Haven, CT 06511. E-mail: song.ma@yale.edu.

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 is 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.[20] We start by presenting two motivating facts. In Figure 2, 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.1, 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 the "climbing up" period. In Figure A.1 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 firms' 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.2 shows the distribution of patent-level half lives 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 different technology spaces. Figure A.3 shows the

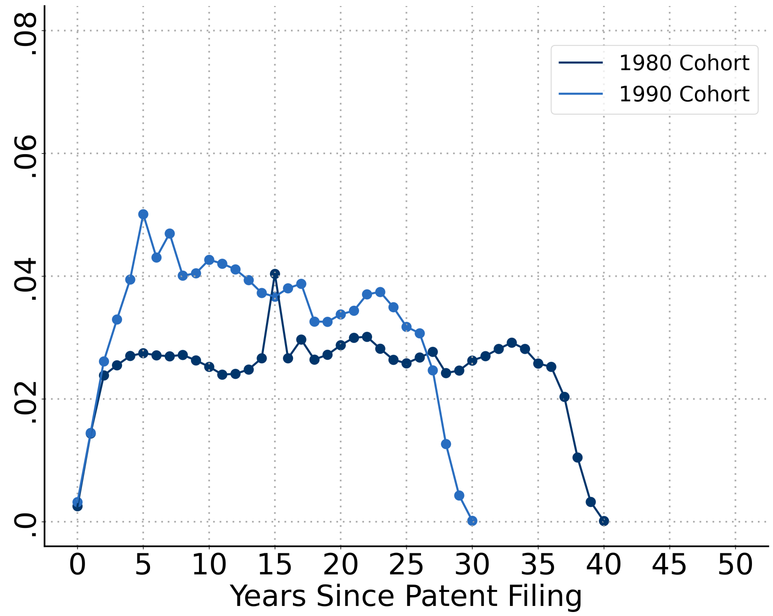
[20]This intuition is also used in bibliometrics and scientometrics, which use citation patterns of patents and papers to track technology evolution.

half lives of patents summarized by the Fama-French 48 industries, and in Appendix Figure A.4 we show those differences across different technological fields categorized by the International Patent Classification (IPC).

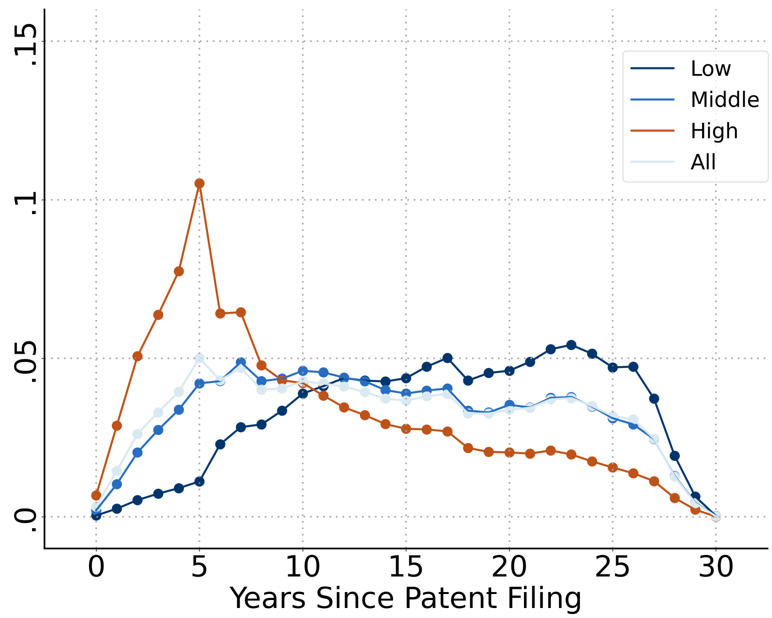
One caveat is that the process of citing patents could be noisy (Roach and Cohen, 2013). Most noticeably, a large portion of citations are so-called examiner-citations, which are inserted by patent examiners but not the patent applicants or their hired professionals (Alcácer, Gittelman, and Sampat, 2009). 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 that the correlation of the two versions of obsolescence with and without examiner patents is 0.94.

Do the citations made by each patent signal the technological evolution and innovation quality? We find evidence consistent with this conjecture. A patent's backward citation is informative of the quality and innovativeness of the patent itself. We show this in our context and also lean on the literature that explores a similar question. If we simply repeat Figure 2 and check if breakthrough innovative patents (as identified using Kelly et al. (2021)) cite past patents of different ages, we do see a sharp difference, as shown in Figure A.5.

When we look deeper, we see that the more innovative patents cite past patents that are less obsolete, while the less innovative patents cite patents that are more obsolete. Specifically, we find that more innovative patents cite patents when these cited patents are on their upward citation trend. For example, in Figure A.6, we find that the more innovative patents cite patents that on average experience an increase in citations in the previous year, and have a low obsolescence score (as constructed using the same logic in the paper but at a patent level).



(a) Average Forward Citation Dynamic



(b) Heterogeneity in Forward Citation Dynamic

Figure A.1. 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. Panel (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 firms' 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.

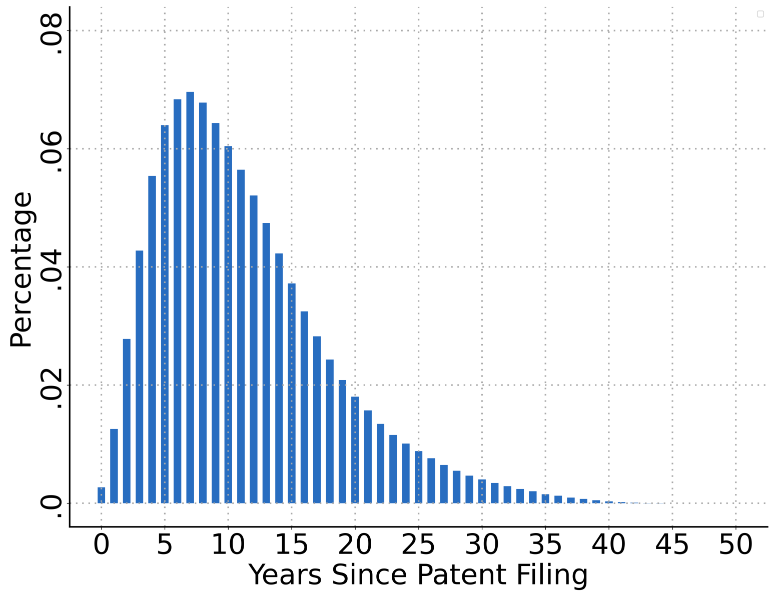


Figure A.2. Distribution of Patents' Half-Lives

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 receive half of the total citations received by the patent to date.

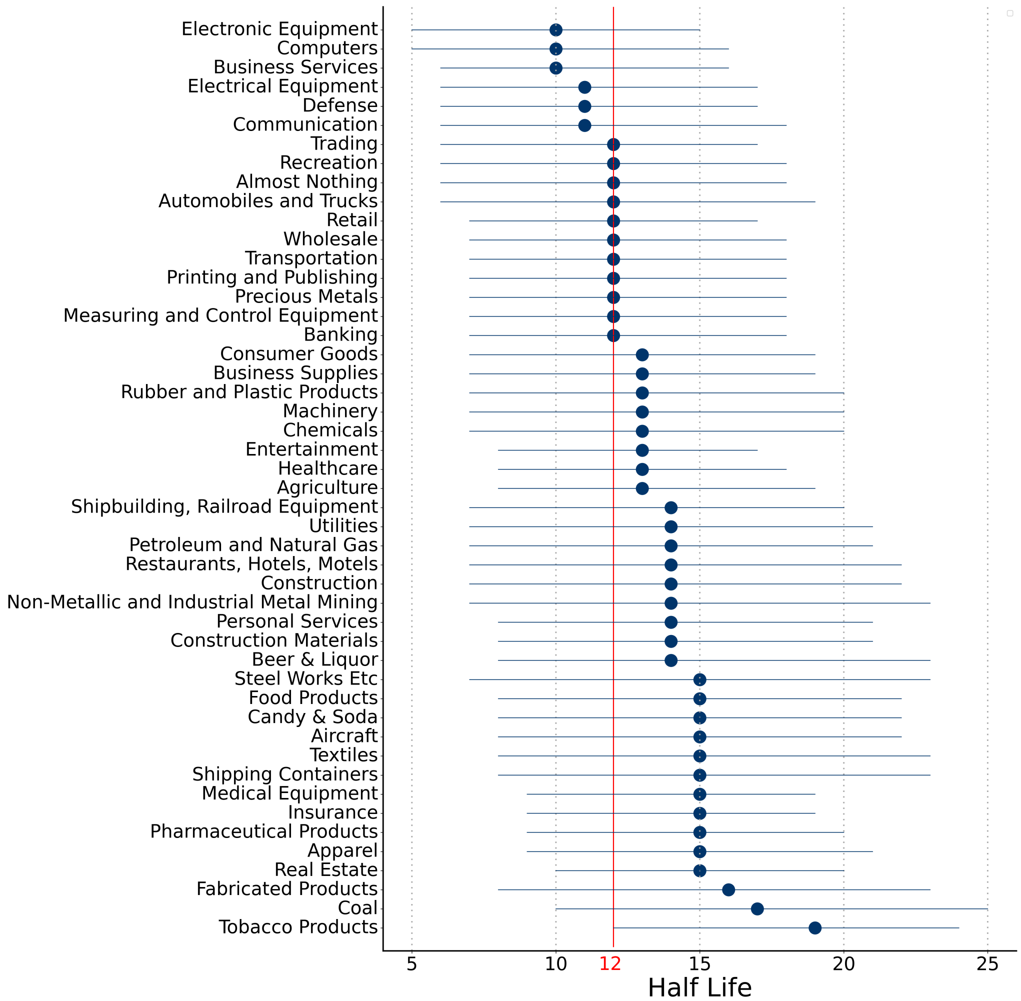


Figure A.3. Dynamics of Citations Received By Each Patent—Heterogeneity

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.

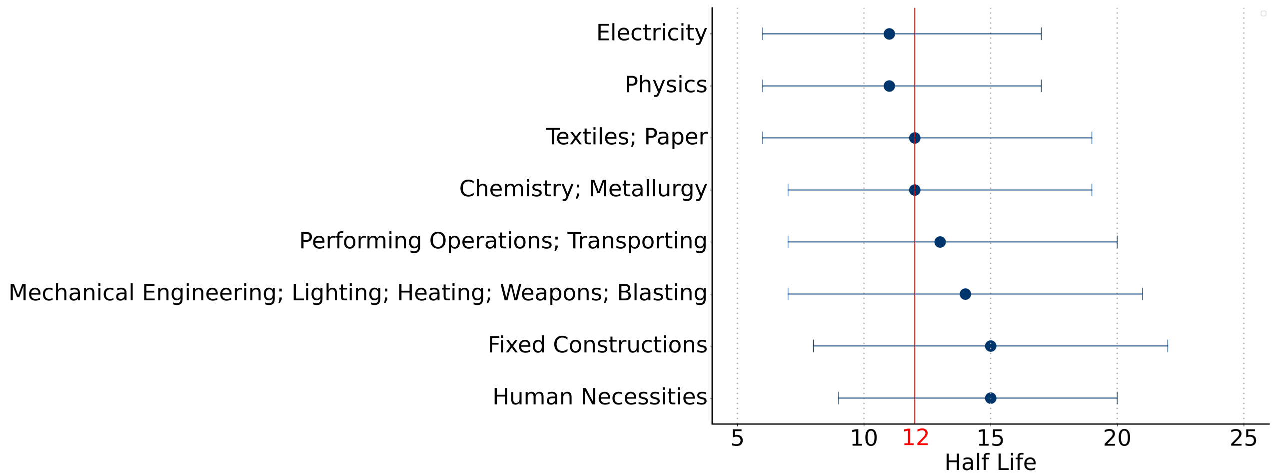


Figure A.4. Patent Citation Half-Lives By International Patent Classification Categories

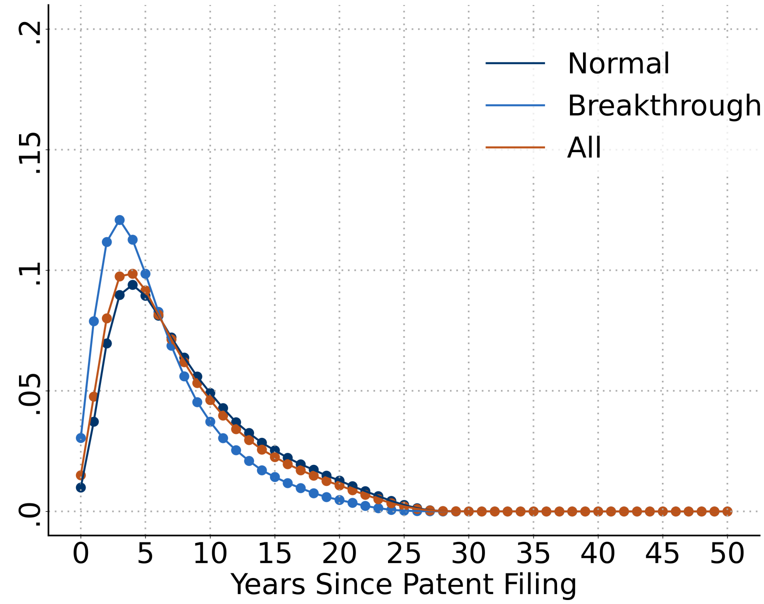


Figure A.5. Heterogeneity in Backward Citation Dynamics

Notes. This figure presents the heterogeneity in backward citation dynamics. The "breakthrough" patents are obtained from Kelly et al. (2021), which is available for patents filed up to 2002. The patent sample contains those patents filed before 2002 with at least 10 backward citations and no more than 1000 backward citations.

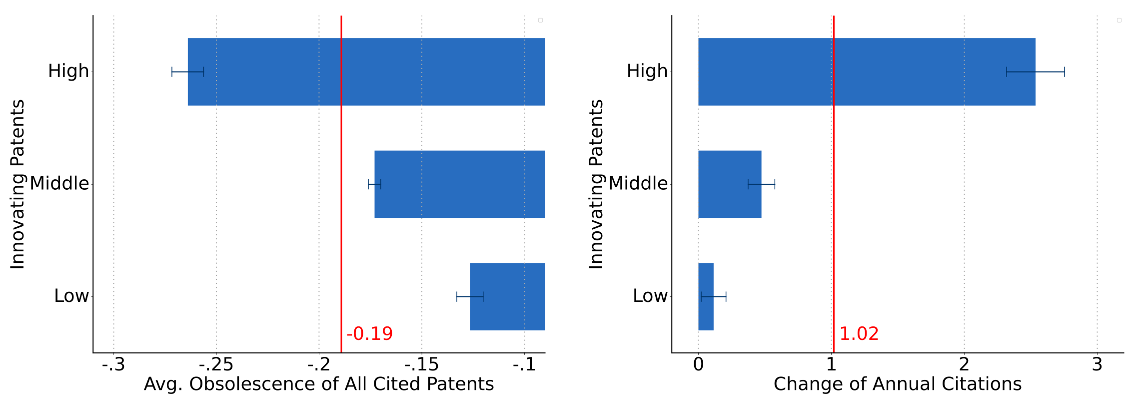


Figure A.6. Characteristics of Patents' Backward Citations

Notes. This figure plots the characteristics of patents cited by patents categorized based on their own innovativeness (based on within-cohort forward citations). The left panel plots the average level of obsolescence at the time the new patents cite the old patents, and the right panel plots the change of annual citations at the time of citing.

A.2. Mathematical Formulation of the *Obsolescence* Measure

In this Appendix, we provide a mathematical formulation of the *Obsolescence* measure, and we use the co-citation matrix as an important tool for this formalization.

Here we define the *Obsolescence* measure in the matrix form. Suppose there are N patents in the world to date, and they are numbered 1, 2, ... N—they cite each other in these inventions. There are M patenting firms, and they are indexed as 1, 2, ..., M.

We can define three important matrices:

- **The citation matrix:** Let $\mathbb{C}_\tau = [c_{p_1,p_2}]$ denote the $N \times N$ matrix in which each element c_{p_1,p_2} indicates whether patent p_1 cites p_2 in the patent.
- **The ownership matrix:** Let $\mathbb{F} = [f_1, f_2, \dots, f_N]'$ denote the $N \times 1$ vector in which each element f_p represents the assignee of the patent p
- **The timing matrix:** For each patent p, it is filed at year t_p by its assignee firm f_p. Let $\mathbb{T} = [t_1, t_2, \dots, t_N]'$ denote the $N \times 1$ vector in which its p-th element represents the filing year of patent p.

Our objective is to represent the *Obsolescence* in the matrix form. Note that the measure for each firm f at year t, with obsolescence horizon ω, is defined as:

$$Obsolescence^{\omega}_{f,t} = -\left[\ln(1 + Cit_t(TechBase_{f,t-\omega})) - \ln(1 + Cit_{t-\omega}(TechBase_{f,t-\omega}))\right], \quad \text{(A4)}$$

where $Cit_t(TechBase_{f,t-\omega})$ is the number of citations received at year t by the patents in the technology base of firm f in year t_b, where the technology base is defined as all the cited patents by a firm's own patents. For now—we will ignore the restrictions that exclude the focal firm's own patents from the base and exclude the focal firm's own citations to the base. This will simplify the exposition of the idea and will be introduced later.

Transforming to Matrix Form: An alternative way to think about the above $Cit_{t/t-\omega}(TechBase_{f,t-\omega})$ operation—namely citations to a firm's technology base—is that we essentially need to calculate the "co-citations" between (i) a firm's past innovation up to $t-\omega$ and (ii) the concurrent innovation that happens in year t or $t-\omega$.

$$Cit_t(TechBase_{f,t-\omega}) = \underbrace{\mathbb{1}(\mathbb{F}=f \;\&\; \mathbb{T}\leq t-\omega)'}_{\text{Patents owned by firm f at } t-\omega} \cdot \mathbb{C}\mathbb{C}' \cdot \underbrace{\mathbb{1}(\mathbb{T}=t)}_{\text{Concurrent innovation in year } t}, \tag{A5}$$

where $\mathbb{1}:\mathbb{R}^N \rightarrow \mathbb{R}^N$ is the matrix element-wise indicator operator. To understand Equation (A5), first note that $\mathbb{C}\mathbb{C}'$ is the co-citation matrix in which each element (p_1, p_2) represents the number of patents cited by the two patents p_1 and p_2. The indicator function $\mathbb{1}(\mathbb{T}=t)$ represents all the patents filed in year t and $\mathbb{1}(\mathbb{F}=f \;\&\; \mathbb{T}\leq t-\omega)$ represents the patents filed by firm f up to year $t-\omega$. Thus, $Cit_t(TechBase_{f,t-\omega})$ captures the number of co-citations made by the patents at year t and the patents filed by firm f up to year $t-\omega$. We can similarly define

$$Cit_{t-\omega}(TechBase_{f,t-\omega}) = \underbrace{\mathbb{1}(\mathbb{F}=f \;\&\; \mathbb{T}\leq t-\omega)'}_{\text{Patents owned by firm f at } t-\omega} \cdot \mathbb{C}\mathbb{C}' \cdot \underbrace{\mathbb{1}(\mathbb{T}=t-\omega)}_{\text{Concurrent innovation in year } t-\omega}, \tag{A6}$$

However, as mentioned above, the definition in Eq. (A5) is slightly different from the one we used in the paper, which included a few restrictive adjustments.

1. **Exclude focal firms' own patents from the base:** First we do not consider the co-citations to firms' own patents in the technology base in the paper. Thus, we need to drop those citations in the citation matrix. To do this, we need to use a modified version of the co-citation matrix, $\mathbb{C}[\mathbb{C}\odot(\mathbb{J}_N\cdot\mathbb{1}(\mathbb{F}\neq f)')]'$, where $\odot$ is the Hadamard product operator and $\mathbb{J}_N$ is the $N\times 1$ matrix of ones. Here, the Hadamard product operation drops all the co-citations to firms' own patents in the technology base.

2. **Exclude focal firms' own citation to the base:** In the paper, we also do not consider the co-citations from firms' own patents. Thus, we need to drop those firms' own patents filed in year t by using $\mathbb{1}(\mathbb{F}\neq f \;\&\; \mathbb{T}=t)$.

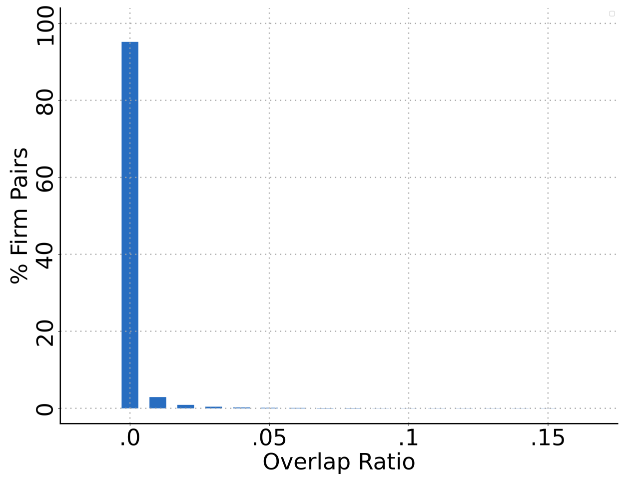
Therefore, after considering the adjustments in the first two points, we have a modified version of $Cit_t(TechBase_{f,t-\omega})$:

$$Cit_t(TechBase_{f,t-\omega}) = \mathbb{1}(\mathbb{F}=f \;\&\; \mathbb{T}\leq t-\omega)'\cdot\mathbb{C}[\mathbb{C}\odot(\mathbb{J}_N\cdot\mathbb{1}(\mathbb{F}\neq f)')]'\cdot\mathbb{1}(\mathbb{F}\neq f \;\&\; \mathbb{T}=t). \tag{A7}$$

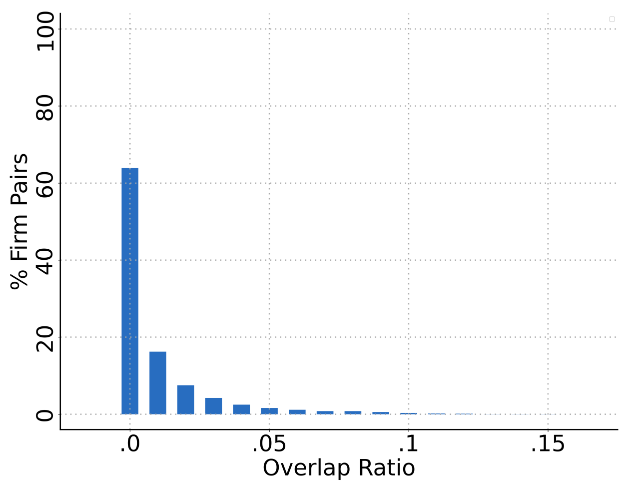
Plugging Equation (A7) into Equation (A4), we obtain the *Obsolescence* measure with duplicated technology base, which is the one we use in Table A.16.

Finally, the *Obsolescence* measure in the original formulation uses a de-duplicated technology base. That is, if multiple firms' patents cite the same patent, we only consider it once in the technology base. However, the matrix form of the *Obsolescence* measure double counts the co-citations to those patents and we have no good way to deal with this under the matrix form.

A.3. Additional Results



(a) All Firms with Patents



(b) Firms with > 100 Patents

Figure A.7. 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. 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 A.2. Robustness: Technological Obsolescence and Firm Growth - Without Keeping the Same Observations Across Different Horizons

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)
R^2	0.214	0.239	0.246	0.246	0.250
Observations	29,319	27,562	25,980	23,685	21,605
			Output		
$Obsolescence_t$	-0.010***	-0.017***	-0.022***	-0.026**	-0.032**
	(0.003)	(0.005)	(0.008)	(0.010)	(0.013)
R^2	0.171	0.192	0.199	0.201	0.206
Observations	30,846	28,972	27,296	24,830	22,621
			Capital		
$Obsolescence_t$	-0.012***	-0.023***	-0.033***	-0.043***	-0.052***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.012)
R^2	0.160	0.182	0.189	0.195	0.199
Observations	31,579	29,655	27,921	25,353	23,037
			Labor		
$Obsolescence_t$	-0.006***	-0.012***	-0.017**	-0.018**	-0.019*
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
R^2	0.151	0.160	0.164	0.169	0.177
Observations	31,494	29,564	27,847	26,182	23,818
			TFP		
$Obsolescence_t$	-0.008***	-0.012***	-0.014***	-0.015***	-0.014**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.007)
R^2	0.200	0.262	0.304	0.323	0.334
Observations	23,781	22,246	20,957	19,109	17,443

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 1. 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, 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 A.3. Robustness of Obsolescence Measure - Horizons ω = 1

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.006*	-0.013***	-0.018***	-0.021***	-0.022***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)
Citation-Weighted Patents$_t$ (CW)	0.003	0.007	0.011	0.010	0.013
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.027**	0.036***	0.046***	0.055***
	(0.007)	(0.011)	(0.014)	(0.016)	(0.018)
R^2	0.253	0.272	0.271	0.265	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.009***	-0.014***	-0.022***	-0.024***	-0.031***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.004	-0.004	-0.006	-0.006	-0.005
	(0.004)	(0.007)	(0.010)	(0.012)	(0.015)
Patent Value$_t$ (SM)	0.014**	0.022**	0.030**	0.036*	0.047**
	(0.006)	(0.011)	(0.014)	(0.019)	(0.020)
R^2	0.202	0.212	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.011***	-0.017***	-0.021***	-0.026***	-0.035***
	(0.002)	(0.004)	(0.005)	(0.007)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.011***	-0.012*	-0.010	-0.011
	(0.002)	(0.004)	(0.006)	(0.009)	(0.010)
Patent Value$_t$ (SM)	0.017***	0.029***	0.037***	0.043***	0.051***
	(0.004)	(0.008)	(0.012)	(0.016)	(0.018)
R^2	0.184	0.202	0.206	0.205	0.202
			Labor (N =23,511)		
$Obsolescence_t$	-0.006***	-0.011***	-0.014***	-0.019***	-0.023***
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.006	-0.007	-0.009	-0.012
	(0.003)	(0.005)	(0.007)	(0.010)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.029**	0.034**
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.003	-0.004	-0.007**	-0.011**	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Citation-Weighted Patents$_t$ (CW)	0.001	0.007	0.010	0.007	0.007
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.024**	0.030***	0.033***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.238	0.295	0.331	0.346	0.350

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 4.

Table A.4. Robustness of Obsolescence Measure—Horizons ω = 3

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.010***	-0.018***	-0.021***	-0.024***	-0.023**
	(0.003)	(0.004)	(0.006)	(0.008)	(0.009)
Citation-Weighted Patents$_t$ (CW)	0.003	0.006	0.010	0.009	0.012
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.027**	0.035***	0.046***	0.055***
	(0.007)	(0.011)	(0.014)	(0.016)	(0.018)
R^2	0.254	0.272	0.272	0.265	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.008***	-0.015***	-0.021***	-0.024***	-0.027***
	(0.003)	(0.005)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.005	-0.006	-0.007	-0.006
	(0.004)	(0.007)	(0.010)	(0.012)	(0.014)
Patent Value$_t$ (SM)	0.014**	0.022**	0.029**	0.035*	0.047**
	(0.006)	(0.010)	(0.014)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.012***	-0.019***	-0.028***	-0.038***	-0.046***
	(0.002)	(0.004)	(0.007)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.012***	-0.013**	-0.012	-0.012
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.029***	0.036***	0.042***	0.050***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.018)
R^2	0.184	0.202	0.207	0.207	0.203
			Labor (N =23,511)		
$Obsolescence_t$	-0.006***	-0.011***	-0.015**	-0.019**	-0.021**
	(0.002)	(0.004)	(0.006)	(0.008)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.007	-0.008	-0.009	-0.013
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.028**	0.033**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.005*	-0.008**	-0.011**	-0.015***	-0.016***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
Citation-Weighted Patents$_t$ (CW)	0.001	0.007	0.009	0.006	0.006
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.024**	0.030***	0.033***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

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 4.

Table A.5. 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)
R^2	0.1575	0.1330	0.1286	0.1285	0.1308
Observations	30,013	30,013	30,013	30,013	30,013

Notes. This table examines the relation between *Obsolescence* and firm bankruptcy (Chapter 11) using the same design as in Table 4 in the main text.

Table A.6. Technological Obsolescence and Growth, Isolating Variations in *Obsolescence*

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.016***	-0.027***	-0.030***	-0.032***	-0.029**
	(0.003)	(0.006)	(0.008)	(0.010)	(0.012)
$Citation\text{-}Weighted\ Patents_t$ (CW)	0.002	0.004	0.008	0.006	0.010
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
$Patent\ Value_t$ (SM)	0.016**	0.025**	0.034**	0.044***	0.054***
	(0.007)	(0.011)	(0.013)	(0.016)	(0.018)
R^2	0.255	0.273	0.272	0.266	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.009***	-0.020***	-0.026***	-0.033***	-0.034**
	(0.003)	(0.006)	(0.009)	(0.011)	(0.014)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.005	-0.006	-0.008	-0.008	-0.008
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
$Patent\ Value_t$ (SM)	0.013**	0.021**	0.028**	0.034*	0.045**
	(0.005)	(0.010)	(0.013)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.012***	-0.022***	-0.031***	-0.038***	-0.043***
	(0.003)	(0.005)	(0.008)	(0.011)	(0.014)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.010***	-0.013***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
$Patent\ Value_t$ (SM)	0.016***	0.028***	0.035***	0.041***	0.048***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.018)
R^2	0.184	0.202	0.207	0.206	0.202
			Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.011**	-0.017**	-0.021**	-0.021*
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Citation\text{-}Weighted\ Patents_t$ (CW)	-0.005*	-0.007	-0.009	-0.010	-0.014
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
$Patent\ Value_t$ (SM)	0.011***	0.017**	0.022**	0.027**	0.032**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.009***	-0.015***	-0.019***	-0.021***	-0.019***
	(0.003)	(0.005)	(0.006)	(0.006)	(0.007)
$Citation\text{-}Weighted\ Patents_t$ (CW)	0	0.005	0.007	0.004	0.005
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
$Patent\ Value_t$ (SM)	0.014*	0.019	0.023**	0.029***	0.032***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.332	0.347	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity using a new construction. Specifically, this approach reconstructs the *Obsolescence* measure with one modification: when tracking changes in citations between $t-\tau$ and t, we impute the citations changes to be zero for patents in the base that experienced a growth of citations over this time window. The table design follows that in Table 6.

Table A.7. 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$_t$	-0.019***	-0.005	-0.023***	-0.008	-0.021***	-0.024
	(0.007)	(0.007)	(0.007)	(0.005)	(0.007)	(0.015)
Citation-Weighted Patents$_t$ (CW)	0.009	0.011	0.009	0.011	0.007	0.014
	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)	(0.017)
Patent Value$_t$ (SM)	0.035***	0.036***	0.035***	0.036***	0.037**	0.047***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.013)
R^2	0.272	0.271	0.272	0.271	0.246	0.391
Observations	21,274	21,274	21,274	21,274	15,513	5,761
			Output			
Obsolescence$_t$	-0.020***	-0.004	-0.020***	-0.007	-0.022**	-0.015
	(0.008)	(0.007)	(0.008)	(0.005)	(0.009)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.007	-0.006	-0.007	-0.006	-0.015	0.030**
	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.012)
Patent Value$_t$ (SM)	0.029**	0.030**	0.029**	0.030**	0.031**	0.039***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.012)
R^2	0.213	0.212	0.213	0.212	0.192	0.360
Observations	22,358	22,358	22,358	22,358	16,564	5,794
			Capital			
Obsolescence$_t$	-0.028***	-0.014**	-0.032***	-0.009*	-0.036***	-0.013
	(0.007)	(0.006)	(0.008)	(0.006)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.014**	-0.012*	-0.014**	-0.012*	-0.017***	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.013)
Patent Value$_t$ (SM)	0.036***	0.037***	0.036***	0.037***	0.038***	0.039***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
R^2	0.208	0.205	0.208	0.205	0.191	0.306
Observations	22,873	22,873	22,873	22,873	17,022	5,851
			Labor			
Obsolescence$_t$	-0.012**	-0.005	-0.017**	-0.005	-0.016**	-0.005
	(0.006)	(0.006)	(0.007)	(0.005)	(0.008)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.008	-0.008	-0.009	-0.008	-0.012*	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)
Patent Value$_t$ (SM)	0.023**	0.024**	0.023**	0.023**	0.025**	0.025***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
R^2	0.184	0.184	0.185	0.184	0.159	0.312
Observations	23,511	23,511	23,511	23,511	17,525	5,986
			TFP			
Obsolescence$_t$	-0.011***	-0.006	-0.011**	-0.007*	-0.013**	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Citation-Weighted Patents$_t$ (CW)	0.009	0.010	0.008	0.010	0.002	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Patent Value$_t$ (SM)	0.024**	0.024**	0.024**	0.024**	0.027**	0.011*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.006)
R^2	0.331	0.331	0.331	0.331	0.306	0.478
Observations	16,639	16,639	16,639	16,639	12,804	3,835

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 4, only the $t+3$ horizon is reported.

Table A.8. Technological Obsolescence and Growth, 20-Year Rolling Window for the Technology Base

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
Obsolescence$_t$	-0.012***	-0.020***	-0.023***	-0.026***	-0.026**
	(0.003)	(0.005)	(0.008)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	0.002	0.005	0.009	0.007	0.011
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.026**	0.035***	0.045***	0.054***
	(0.007)	(0.011)	(0.013)	(0.016)	(0.018)
R^2	0.254	0.272	0.272	0.265	0.258
			Output (N =22,358)		
Obsolescence$_t$	-0.008**	-0.016***	-0.021**	-0.026**	-0.030**
	(0.004)	(0.006)	(0.009)	(0.011)	(0.014)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.006	-0.007	-0.008	-0.008
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
Patent Value$_t$ (SM)	0.014**	0.021**	0.029**	0.035*	0.046**
	(0.006)	(0.010)	(0.014)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
Obsolescence$_t$	-0.012***	-0.021***	-0.030***	-0.039***	-0.046***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.013***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.028***	0.036***	0.041***	0.049***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.018)
R^2	0.185	0.203	0.208	0.207	0.203
			Labor (N =23,511)		
Obsolescence$_t$	-0.006**	-0.010**	-0.015**	-0.017**	-0.018*
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.007	-0.009	-0.010	-0.014
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.028**	0.033**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
Obsolescence$_t$	-0.005*	-0.008*	-0.012***	-0.016***	-0.015**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0	0.006	0.008	0.005	0.006
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.023**	0.030***	0.033***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity. The design follows that in Table 4.

Table A.9. Technological Obsolescence and Growth, Technology Base with Depreciation Rate of 0.9

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.013***	-0.021***	-0.024***	-0.027***	-0.027**
	(0.003)	(0.005)	(0.008)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	0.002	0.005	0.008	0.007	0.011
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.026**	0.035***	0.045***	0.054***
	(0.007)	(0.011)	(0.013)	(0.016)	(0.018)
R^2	0.254	0.273	0.272	0.265	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.009**	-0.017***	-0.022**	-0.027**	-0.031**
	(0.004)	(0.006)	(0.009)	(0.011)	(0.013)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.006	-0.007	-0.008	-0.007
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
Patent Value$_t$ (SM)	0.013**	0.021**	0.029**	0.035*	0.046**
	(0.006)	(0.010)	(0.014)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.013***	-0.022***	-0.031***	-0.040***	-0.048***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.013***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.028***	0.036***	0.041***	0.049***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.018)
R^2	0.185	0.203	0.208	0.207	0.204
			Labor (N =23,511)		
$Obsolescence_t$	-0.006***	-0.011**	-0.015**	-0.018**	-0.019*
	(0.002)	(0.004)	(0.007)	(0.008)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.007	-0.009	-0.010	-0.014
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.028**	0.033**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.006*	-0.009**	-0.013***	-0.017***	-0.015**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0	0.006	0.008	0.005	0.005
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.023**	0.030***	0.033***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity. The design follows that in Table 4.

Table A.10. Technological Obsolescence and Growth, Deflated by Patents Per Capita

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.012***	-0.019***	-0.023***	-0.026***	-0.026**
	(0.003)	(0.005)	(0.008)	(0.009)	(0.011)
Citation-Weighted Patents$_t$ (CW)	0.002	0.005	0.009	0.007	0.011
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.026**	0.035***	0.045***	0.055***
	(0.007)	(0.011)	(0.014)	(0.016)	(0.018)
R^2	0.254	0.272	0.272	0.265	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.008**	-0.016***	-0.021**	-0.026**	-0.030**
	(0.004)	(0.006)	(0.009)	(0.011)	(0.013)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.006	-0.007	-0.008	-0.007
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
Patent Value$_t$ (SM)	0.014**	0.021**	0.029**	0.035*	0.046**
	(0.006)	(0.010)	(0.014)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.211	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.012***	-0.021***	-0.030***	-0.039***	-0.045***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.013***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.028***	0.036***	0.042***	0.049***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.018)
R^2	0.185	0.203	0.208	0.207	0.203
			Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.010**	-0.015**	-0.018**	-0.019*
	(0.002)	(0.004)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.007	-0.009	-0.010	-0.014
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.028**	0.033**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.006*	-0.008*	-0.012**	-0.015***	-0.014**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0	0.006	0.008	0.005	0.006
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.024**	0.030***	0.033***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

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 4.

Table A.11. Technological Obsolescence and Growth, Firm FE ($t+5$)

	(1) Profits$_{t+5}$	(2) Output$_{t+5}$	(3) Capital$_{t+5}$	(4) Labor$_{t+5}$	(5) TFP$_{t+5}$
$Obsolescence_t$	-0.026***	-0.016*	-0.029***	-0.017**	-0.008
	(0.009)	(0.008)	(0.008)	(0.008)	(0.005)
R^2	0.964	0.970	0.976	0.965	0.640
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	17,927	17,974	17,946	17,868	15,792

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 4.

Table A.12. Technological Obsolescence and Growth—Dropping Competitors' Patents

	Drop Patents from Hoberg-Phillips Competitors			Drop Patents from SIC-3 Competitors		
Time Horizon =	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
			Profits (N =21,274)			
Obsolescence$_t$	-0.011***	-0.021***	-0.024**	-0.012***	-0.021***	-0.025**
	(0.003)	(0.007)	(0.010)	(0.003)	(0.007)	(0.011)
Citation-Weighted Patents$_t$ (CW)	0.002	0.009	0.011	0.002	0.009	0.011
	(0.005)	(0.011)	(0.016)	(0.005)	(0.011)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.035***	0.055***	0.017**	0.035***	0.055***
	(0.007)	(0.013)	(0.018)	(0.007)	(0.014)	(0.018)
R^2	0.254	0.272	0.258	0.254	0.272	0.258
			Output (N =22,358)			
Obsolescence$_t$	-0.008**	-0.019**	-0.026**	-0.008**	-0.019**	-0.027**
	(0.004)	(0.008)	(0.013)	(0.004)	(0.008)	(0.013)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.007	-0.007	-0.005	-0.007	-0.007
	(0.004)	(0.009)	(0.014)	(0.004)	(0.009)	(0.014)
Patent Value$_t$ (SM)	0.014**	0.029**	0.046**	0.014**	0.029**	0.046**
	(0.006)	(0.013)	(0.019)	(0.006)	(0.014)	(0.019)
R^2	0.202	0.213	0.212	0.202	0.213	0.212
			Capital (N =22,873)			
Obsolescence$_t$	-0.012***	-0.030***	-0.044***	-0.012***	-0.030***	-0.044***
	(0.003)	(0.008)	(0.012)	(0.002)	(0.007)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.014**	-0.014	-0.010***	-0.014**	-0.014
	(0.002)	(0.006)	(0.010)	(0.002)	(0.006)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.036***	0.049***	0.016***	0.036***	0.049***
	(0.004)	(0.012)	(0.018)	(0.004)	(0.012)	(0.018)
R^2	0.184	0.208	0.203	0.185	0.208	0.203
			Labor (N =23,511)			
Obsolescence$_t$	-0.005**	-0.013*	-0.013	-0.006**	-0.013*	-0.015
	(0.002)	(0.007)	(0.010)	(0.002)	(0.007)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.008	-0.013	-0.005*	-0.008	-0.014
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.023**	0.033**	0.011***	0.023**	0.033**
	(0.003)	(0.009)	(0.014)	(0.003)	(0.009)	(0.014)
R^2	0.173	0.184	0.183	0.173	0.185	0.183
			TFP (N =16,639)			
Obsolescence$_t$	-0.006*	-0.011**	-0.011**	-0.005	-0.010**	-0.013**
	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0	0.008	0.006	0.001	0.008	0.006
	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.024**	0.033***	0.015*	0.024**	0.033***
	(0.008)	(0.011)	(0.010)	(0.008)	(0.011)	(0.010)
R^2	0.239	0.331	0.350	0.239	0.331	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity. The design follows that in Table 4 with abbreviation. The key difference with Table 4 is that when constructing *Obsolescence*, the Technology Base excludes patents from industry competitors defined using both Hoberg-Phillips categorizations (Hoberg and Phillips, 2016) and competitors in the same 3-digit SIC industries.

Table A.13. Robustness of *Obsolescence* Measure—Only General Patents In the Base

	High-Generality Patents			Low-Generality Patents		
Time Horizon =	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
				Profits (N =21,274)		
$Obsolescence_t$	-0.011***	-0.021***	-0.025***	-0.006**	-0.012**	-0.014
	(0.003)	(0.007)	(0.009)	(0.003)	(0.006)	(0.010)
Citation-Weighted Patents$_t$ (CW)	0.003	0.010	0.012	0.003	0.011	0.013
	(0.005)	(0.011)	(0.016)	(0.005)	(0.011)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.035***	0.054***	0.017**	0.035***	0.055***
	(0.007)	(0.013)	(0.018)	(0.007)	(0.014)	(0.018)
R^2	0.254	0.272	0.258	0.253	0.271	0.257
				Output (N =22,358)		
$Obsolescence_t$	-0.006*	-0.019**	-0.025**	-0.006**	-0.012*	-0.012
	(0.003)	(0.008)	(0.011)	(0.003)	(0.006)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.007	-0.006	-0.005	-0.006	-0.005
	(0.004)	(0.009)	(0.014)	(0.004)	(0.010)	(0.014)
Patent Value$_t$ (SM)	0.014**	0.029**	0.046**	0.014**	0.030**	0.047**
	(0.006)	(0.014)	(0.019)	(0.006)	(0.014)	(0.020)
R^2	0.202	0.213	0.212	0.202	0.213	0.211
				Capital (N =22,873)		
$Obsolescence_t$	-0.010***	-0.025***	-0.038***	-0.008***	-0.016***	-0.023***
	(0.002)	(0.007)	(0.011)	(0.002)	(0.006)	(0.009)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.013**	-0.012	-0.009***	-0.012**	-0.011
	(0.002)	(0.006)	(0.010)	(0.002)	(0.006)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.036***	0.049***	0.016***	0.037***	0.051***
	(0.004)	(0.012)	(0.018)	(0.004)	(0.012)	(0.018)
R^2	0.184	0.207	0.203	0.183	0.206	0.201
				Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.015**	-0.018**	-0.005**	-0.011**	-0.012
	(0.002)	(0.006)	(0.009)	(0.002)	(0.005)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.008	-0.013	-0.005*	-0.008	-0.013
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.023**	0.033**	0.011***	0.023**	0.034**
	(0.003)	(0.009)	(0.014)	(0.003)	(0.009)	(0.014)
R^2	0.173	0.185	0.184	0.173	0.184	0.183
				TFP (N =16,639)		
$Obsolescence_t$	-0.007**	-0.012***	-0.014***	-0.003	-0.007*	-0.005
	(0.003)	(0.005)	(0.005)	(0.002)	(0.004)	(0.005)
Citation-Weighted Patents$_t$ (CW)	0	0.009	0.006	0.001	0.010	0.007
	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.024**	0.033***	0.015*	0.024**	0.033***
	(0.008)	(0.011)	(0.010)	(0.008)	(0.011)	(0.010)
R^2	0.239	0.331	0.350	0.238	0.331	0.349

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 4, only the $t+1$, $t+3$, and $t+5$ horizon is reported.

Table A.14. Robustness of *Obsolescence* Measure—Different Components of Technology Base

	Foreign-Country Patents			Non-Corporation Patents			Standard Essential Patents		
Time Horizon =	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
				Profits (N =21,274)					
Obsolescence$_t$	-0.010***	-0.022***	-0.029***	-0.002	-0.004	-0.005	0.001	-0.016*	-0.021*
	(0.003)	(0.006)	(0.009)	(0.003)	(0.007)	(0.009)	(0.004)	(0.009)	(0.012)
Citation-Weighted Patents$_t$ (CW)	0.003	0.009	0.011	0.003	0.011	0.013	0.003	0.011	0.013
	(0.005)	(0.011)	(0.016)	(0.005)	(0.011)	(0.016)	(0.005)	(0.011)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.035***	0.054***	0.017**	0.036***	0.055***	0.017**	0.036***	0.055***
	(0.007)	(0.013)	(0.018)	(0.007)	(0.014)	(0.018)	(0.007)	(0.014)	(0.018)
R^2	0.254	0.272	0.258	0.253	0.271	0.257	0.253	0.271	0.257
				Output (N =22,358)					
Obsolescence$_t$	-0.007**	-0.018**	-0.027***	-0.004	-0.007	-0.006	-0	-0.019*	-0.025*
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.009)	(0.004)	(0.010)	(0.014)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.007	-0.007	-0.005	-0.006	-0.005	-0.004	-0.006	-0.005
	(0.004)	(0.009)	(0.014)	(0.004)	(0.010)	(0.015)	(0.004)	(0.010)	(0.015)
Patent Value$_t$ (SM)	0.014**	0.029**	0.046**	0.014**	0.030**	0.047**	0.014**	0.030**	0.047**
	(0.006)	(0.014)	(0.019)	(0.006)	(0.014)	(0.020)	(0.006)	(0.014)	(0.020)
R^2	0.202	0.213	0.212	0.202	0.212	0.211	0.202	0.212	0.211
				Capital (N =22,873)					
Obsolescence$_t$	-0.011***	-0.029***	-0.040***	-0.004**	-0.013**	-0.018**	-0.004	-0.012	-0.023*
	(0.002)	(0.006)	(0.010)	(0.002)	(0.006)	(0.009)	(0.004)	(0.009)	(0.013)
Citation-Weighted Patents$_t$ (CW)	-0.009***	-0.014**	-0.013	-0.009***	-0.012**	-0.011	-0.009***	-0.012*	-0.011
	(0.002)	(0.006)	(0.010)	(0.002)	(0.006)	(0.010)	(0.002)	(0.006)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.036***	0.049***	0.017***	0.037***	0.051***	0.017***	0.037***	0.051***
	(0.004)	(0.012)	(0.018)	(0.004)	(0.012)	(0.018)	(0.004)	(0.012)	(0.018)
R^2	0.185	0.208	0.203	0.182	0.205	0.200	0.182	0.205	0.200

	Foreign-Country Patents			Non-Corporation Patents			Standard Essential Patents		
Time Horizon =	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$	$t+1$	$t+3$	$t+5$
				Labor (N =23,511)					
Obsolescence$_t$	-0.005**	-0.013**	-0.015*	-0.004**	-0.009*	-0.006	-0.001	-0.008	-0.021*
	(0.002)	(0.006)	(0.008)	(0.002)	(0.005)	(0.007)	(0.003)	(0.007)	(0.011)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.008	-0.013	-0.005*	-0.008	-0.013	-0.005	-0.008	-0.013
	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.011)	(0.003)	(0.008)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.023**	0.033**	0.011***	0.023**	0.034**	0.011***	0.024**	0.034**
	(0.003)	(0.009)	(0.014)	(0.003)	(0.009)	(0.014)	(0.004)	(0.009)	(0.014)
R^2	0.173	0.185	0.183	0.172	0.184	0.183	0.172	0.184	0.183
				TFP (N =16,639)					
Obsolescence$_t$	-0.006*	-0.014***	-0.015***	-0.002	-0.001	-0.001	-0	-0.013*	-0.009
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.010)
Citation-Weighted Patents$_t$ (CW)	0.001	0.008	0.006	0.001	0.010	0.007	0.001	0.009	0.007
	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.023**	0.033***	0.015*	0.024**	0.033***	0.015*	0.024**	0.033***
	(0.008)	(0.011)	(0.010)	(0.008)	(0.011)	(0.010)	(0.008)	(0.011)	(0.010)
R^2	0.239	0.331	0.350	0.238	0.330	0.349	0.238	0.331	0.349

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 4, only the $t+1$, $t+3$, and $t+5$ horizon is reported.

Table A.15. Robustness of *Obsolescence* Measure—Patents Owned

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.013***	-0.025***	-0.036***	-0.040***	-0.044***
	(0.003)	(0.005)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	0.001	0.003	0.006	0.004	0.007
	(0.004)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.016**	0.024**	0.032**	0.042***	0.051***
	(0.006)	(0.011)	(0.013)	(0.016)	(0.017)
R^2	0.254	0.273	0.274	0.267	0.260
			Output (N =22,358)		
$Obsolescence_t$	-0.008***	-0.016***	-0.022***	-0.022**	-0.022**
	(0.003)	(0.006)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.006	-0.008	-0.009	-0.008
	(0.004)	(0.007)	(0.010)	(0.012)	(0.014)
Patent Value$_t$ (SM)	0.013**	0.020**	0.028**	0.034*	0.045**
	(0.006)	(0.010)	(0.013)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.210	0.211
			Capital (N =22,873)		
$Obsolescence_t$	-0.011***	-0.019***	-0.027***	-0.033***	-0.035***
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.013***	-0.015**	-0.014*	-0.015
	(0.002)	(0.004)	(0.006)	(0.009)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.028***	0.035***	0.040***	0.048***
	(0.004)	(0.008)	(0.011)	(0.015)	(0.017)
R^2	0.184	0.202	0.207	0.206	0.202
			Labor (N =23,511)		
$Obsolescence_t$	-0.006***	-0.012***	-0.015***	-0.017**	-0.019**
	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.008	-0.009	-0.011	-0.015
	(0.003)	(0.005)	(0.008)	(0.010)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.017**	0.022**	0.027**	0.032**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.013)
R^2	0.173	0.182	0.185	0.184	0.184
			TFP (N =16,639)		
$Obsolescence_t$	-0.007*	-0.012**	-0.013**	-0.012*	-0.012*
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0	0.005	0.008	0.005	0.005
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.014*	0.018	0.023**	0.029***	0.032***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity. We use the technological obsolescence as the rate of change in citations made to the firm's own patent portfolio, instead of the technology base. The design follows that in Table 4.

Table A.16. Robustness of *Obsolescence* Measure—Duplicated Technology Base

Time Horizon =	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
			Profits (N =21,274)		
$Obsolescence_t$	-0.011***	-0.018***	-0.021***	-0.024***	-0.024**
	(0.003)	(0.005)	(0.007)	(0.009)	(0.010)
Citation-Weighted Patents$_t$ (CW)	0.002	0.005	0.009	0.007	0.011
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)
Patent Value$_t$ (SM)	0.017**	0.026**	0.035***	0.045***	0.055***
	(0.007)	(0.011)	(0.014)	(0.016)	(0.018)
R^2	0.254	0.272	0.272	0.265	0.258
			Output (N =22,358)		
$Obsolescence_t$	-0.008**	-0.015***	-0.018**	-0.021**	-0.025**
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.005	-0.005	-0.007	-0.007	-0.007
	(0.004)	(0.007)	(0.009)	(0.012)	(0.014)
Patent Value$_t$ (SM)	0.014**	0.021**	0.029**	0.035*	0.046**
	(0.006)	(0.010)	(0.014)	(0.019)	(0.019)
R^2	0.202	0.213	0.213	0.210	0.212
			Capital (N =22,873)		
$Obsolescence_t$	-0.012***	-0.021***	-0.029***	-0.038***	-0.045***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.012)
Citation-Weighted Patents$_t$ (CW)	-0.010***	-0.013***	-0.014**	-0.013	-0.014
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Patent Value$_t$ (SM)	0.016***	0.028***	0.036***	0.042***	0.049***
	(0.004)	(0.008)	(0.012)	(0.015)	(0.018)
R^2	0.185	0.203	0.208	0.207	0.203
			Labor (N =23,511)		
$Obsolescence_t$	-0.006**	-0.010**	-0.013**	-0.014*	-0.015
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)
Citation-Weighted Patents$_t$ (CW)	-0.005*	-0.007	-0.008	-0.010	-0.013
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Patent Value$_t$ (SM)	0.011***	0.018**	0.023**	0.028**	0.033**
	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
R^2	0.173	0.182	0.185	0.184	0.183
			TFP (N =16,639)		
$Obsolescence_t$	-0.006*	-0.009**	-0.012***	-0.014***	-0.012**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Citation-Weighted Patents$_t$ (CW)	0	0.006	0.008	0.005	0.006
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)
Patent Value$_t$ (SM)	0.015*	0.019	0.024**	0.030***	0.033***
	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
R^2	0.239	0.296	0.331	0.346	0.350

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity. We use the 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 4.

Table A.17. Technological Obsolescence and Growth, Controlling For Other Innovation Measures

Panel (a): Controlling for $RETech_t$ and $Tech\ Breadth_t$ from BFH

	(1) Profits$_{t+5}$	(2) Output$_{t+5}$	(3) Capital$_{t+5}$	(4) Labor$_{t+5}$	(5) TFP$_{t+5}$
$Obsolescence_t$	-0.032***	-0.036***	-0.056***	-0.023**	-0.014**
	(0.011)	(0.013)	(0.012)	(0.010)	(0.006)
R^2	0.248	0.205	0.198	0.178	0.348
Industry x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	20,275	21,336	21,820	22,413	15,884

Panel (b): Controlling for $\%\ Breakthrough\ Patents_t$ from KPST

	(1) Profits$_{t+5}$	(2) Output$_{t+5}$	(3) Capital$_{t+5}$	(4) Labor$_{t+5}$	(5) TFP$_{t+5}$
$Obsolescence_t$	-0.032***	-0.033**	-0.050***	-0.020*	-0.016***
	(0.011)	(0.013)	(0.013)	(0.010)	(0.006)
R^2	0.255	0.206	0.201	0.183	0.344
Industry x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	19,611	20,592	21,031	20,841	15,327

Notes. This table examines the relation between *Obsolescence* and firm growth and productivity after adding alternative measures of new innovation. Panel (a) controls for the RETech measures from Bowen III, Frésard, and Hoberg (2023) (BFH), and panel (b) controls for the share of breakthrough patents from Kelly et al. (2021) (KPST). The design follows that in Table 4.

Table A.18. 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 an *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 an *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 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 a non-missing *Obsolescence* measure 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.19. Monthly Returns of Obsolescence-Sorted Portfolios—Equal-Weight Portfolio

Panel (a): Equal-Weight Portfolio, with Factor Models

	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***
	(0.319)	(0.098)	(0.096)	(0.090)	(0.110)	(0.095)	(0.095)	(0.092)
Middle	0.899***	0.167*	0.309***	0.197**	0.144	0.082	0.228**	0.190**
	(0.310)	(0.099)	(0.090)	(0.083)	(0.112)	(0.094)	(0.089)	(0.085)
High	0.757**	-0.032	0.141	0.087	0.031	-0.109	0.078	0.072
	(0.349)	(0.110)	(0.105)	(0.095)	(0.113)	(0.112)	(0.111)	(0.097)
Low–High	0.168*	0.274***	0.237***	0.288***	0.301***	0.310***	0.266***	0.301***
	(0.095)	(0.081)	(0.084)	(0.082)	(0.087)	(0.088)	(0.092)	(0.085)
All	0.864***	0.130	0.279***	0.217***	0.167	0.060	0.218**	0.209**
	(0.322)	(0.094)	(0.087)	(0.080)	(0.104)	(0.091)	(0.088)	(0.081)

Panel (b): Equal-Weight Portfolio, with Factor Models and Sample-Specific Market Factor

	Exret	3F	4F	4F + RMW + CMA	Q5 (HXZ)	$3F^{INT}$	$4F^{INT}$	$4F^{INT}$ + RMW + CMA
Low	0.925***	0.120**	0.113**	0.160***	0.184***	0.143***	0.131**	0.163***
	(0.319)	(0.049)	(0.051)	(0.050)	(0.053)	(0.050)	(0.053)	(0.051)
Middle	0.899***	0.040	0.032	-0.016	-0.029	0.024	0.018	-0.015
	(0.310)	(0.034)	(0.031)	(0.028)	(0.031)	(0.032)	(0.030)	(0.028)
High	0.757**	-0.174***	-0.156***	-0.139***	-0.146***	-0.176***	-0.156***	-0.144***
	(0.349)	(0.043)	(0.046)	(0.043)	(0.044)	(0.046)	(0.050)	(0.045)
Low–High	0.168*	0.294***	0.268***	0.300***	0.329***	0.319***	0.287***	0.308***
	(0.095)	(0.080)	(0.088)	(0.085)	(0.089)	(0.086)	(0.095)	(0.088)

Notes. This table presents equal-weight 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. All other analyses follow Table 9 in the main text.

Table A.20. 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***
	(0.269)	(0.099)	(0.100)	(0.104)	(0.112)	(0.109)	(0.109)	(0.109)
2	0.842***	0.318***	0.329***	0.289***	0.217*	0.333***	0.337***	0.319***
	(0.250)	(0.084)	(0.088)	(0.095)	(0.112)	(0.091)	(0.097)	(0.101)
3	0.649***	0.072	0.107	0.004	-0.125	0.032	0.059	0.020
	(0.249)	(0.085)	(0.089)	(0.088)	(0.092)	(0.089)	(0.094)	(0.090)
4	0.543**	-0.074	-0.023	-0.181*	-0.248**	-0.110	-0.055	-0.166*
	(0.240)	(0.083)	(0.093)	(0.096)	(0.096)	(0.086)	(0.101)	(0.095)
5	0.534**	-0.090	-0.012	-0.181	-0.204	-0.142	-0.062	-0.166
	(0.242)	(0.124)	(0.116)	(0.120)	(0.150)	(0.123)	(0.117)	(0.122)
1-5	0.415**	0.550***	0.484***	0.711***	0.666***	0.634***	0.557***	0.727***
	(0.182)	(0.161)	(0.152)	(0.162)	(0.190)	(0.164)	(0.157)	(0.160)

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***
	(0.323)	(0.105)	(0.105)	(0.101)	(0.117)	(0.104)	(0.107)	(0.101)
2	0.946***	0.238**	0.369***	0.266***	0.198*	0.157*	0.290***	0.262***
	(0.309)	(0.096)	(0.092)	(0.086)	(0.113)	(0.090)	(0.091)	(0.088)
3	0.916***	0.190*	0.339***	0.228**	0.163	0.103	0.256***	0.221**
	(0.307)	(0.108)	(0.098)	(0.094)	(0.127)	(0.104)	(0.097)	(0.096)
4	0.804**	0.042	0.180*	0.101	0.027	-0.026	0.123	0.094
	(0.329)	(0.104)	(0.097)	(0.093)	(0.096)	(0.106)	(0.105)	(0.094)
5	0.754**	-0.048	0.147	0.093	0.052	-0.134	0.076	0.075
	(0.362)	(0.124)	(0.113)	(0.103)	(0.134)	(0.123)	(0.117)	(0.104)
1-5	0.148	0.276***	0.214**	0.305***	0.340***	0.335***	0.268**	0.320***
	(0.115)	(0.097)	(0.096)	(0.097)	(0.107)	(0.103)	(0.104)	(0.099)

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.21. Return Predictive Power of Technological Obsolescence

Panel (a): Value-Weight Portfolio

	Ind-adjret	Size/BM-adjret	Size/BM/Mom-adjret
Low	-0.181	0.178*	0.118*
	(0.174)	(0.096)	(0.070)
Middle	-0.314**	-0.065*	-0.046
	(0.153)	(0.038)	(0.033)
High	-0.222*	-0.129	-0.114**
	(0.124)	(0.091)	(0.058)
Low-High	0.041	0.307*	0.231**
	(0.123)	(0.174)	(0.118)

Panel (b): Equal-Weight Portfolio

	Ind-adjret	Size/BM-adjret	Size/BM/Mom-adjret
Low	0.060	0.051	0.072*
	(0.040)	(0.053)	(0.040)
Middle	0.008	0.044	0.031
	(0.035)	(0.030)	(0.024)
High	-0.071*	-0.110**	-0.113***
	(0.041)	(0.046)	(0.038)
Low-High	0.131**	0.161*	0.185***
	(0.066)	(0.091)	(0.072)

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.22. 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***
	(0.246)	(0.062)	(0.060)	(0.061)	(0.073)	(0.070)	(0.068)	(0.068)
Middle	0.678***	0.108*	0.138**	0.064	-0.054	0.091	0.117*	0.083
	(0.237)	(0.062)	(0.064)	(0.061)	(0.071)	(0.066)	(0.069)	(0.063)
High	0.621***	0.043	0.068	-0.087	-0.084	0.008	0.028	-0.062
	(0.237)	(0.075)	(0.081)	(0.073)	(0.079)	(0.077)	(0.085)	(0.077)
Low-High	0.214**	0.264***	0.262***	0.368***	0.262***	0.302***	0.298***	0.370***
	(0.102)	(0.091)	(0.096)	(0.095)	(0.101)	(0.096)	(0.102)	(0.095)

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***
	(0.319)	(0.093)	(0.092)	(0.088)	(0.111)	(0.091)	(0.093)	(0.088)
Middle	0.848***	0.110	0.256***	0.155*	0.070	0.025	0.176**	0.146*
	(0.312)	(0.097)	(0.086)	(0.079)	(0.102)	(0.092)	(0.086)	(0.081)
High	0.829**	0.079	0.238**	0.195**	0.167	0.015	0.185*	0.188*
	(0.343)	(0.111)	(0.105)	(0.097)	(0.120)	(0.110)	(0.109)	(0.099)
Low-High	0.089	0.124*	0.109	0.121*	0.118*	0.133**	0.115*	0.120*
	(0.068)	(0.065)	(0.067)	(0.066)	(0.065)	(0.067)	(0.069)	(0.065)

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)	(0.065)	(0.069)	(0.079)	(0.076)	(0.073)	(0.075)
Middle	0.678***	0.103*	0.134**	0.040	-0.078	0.079	0.106*	0.058
	(0.234)	(0.058)	(0.059)	(0.057)	(0.071)	(0.062)	(0.064)	(0.060)
High	0.639***	0.058	0.103	-0.038	-0.044	0.024	0.065	-0.014
	(0.241)	(0.079)	(0.084)	(0.080)	(0.086)	(0.081)	(0.090)	(0.082)
Low-High	0.213*	0.283***	0.238**	0.368***	0.289**	0.341***	0.293***	0.374***
	(0.120)	(0.098)	(0.100)	(0.109)	(0.121)	(0.105)	(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***
	(0.322)	(0.095)	(0.093)	(0.087)	(0.107)	(0.092)	(0.094)	(0.087)
Middle	0.849***	0.111	0.254***	0.145*	0.062	0.022	0.171**	0.135
	(0.307)	(0.096)	(0.087)	(0.081)	(0.105)	(0.091)	(0.086)	(0.082)
High	0.831**	0.083	0.248**	0.213**	0.184	0.020	0.197*	0.207**
	(0.347)	(0.113)	(0.106)	(0.097)	(0.121)	(0.112)	(0.109)	(0.098)
Low-High	0.087	0.120*	0.096	0.104	0.104	0.130*	0.103	0.104
	(0.074)	(0.070)	(0.069)	(0.071)	(0.070)	(0.073)	(0.072)	(0.070)

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 parentheses.

Table A.23. 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***	-0.070*	-0.080**	-0.082***	-0.067***
	(0.079)	(0.058)	(0.053)	(0.035)	(0.037)	(0.031)	(0.031)	(0.026)
Size		-0.182	-0.159	-0.180*		-0.235***	-0.204**	-0.204**
		(0.121)	(0.118)	(0.106)		(0.079)	(0.081)	(0.082)
$\log(BM)$		0.132*	0.157**	0.132**		0.094*	0.065	0.078*
		(0.076)	(0.074)	(0.063)		(0.050)	(0.047)	(0.042)
$Ret(-1,0)$		-0.376***	-0.405***	-0.444***		-0.532***	-0.552***	-0.611***
		(0.094)	(0.090)	(0.079)		(0.060)	(0.062)	(0.064)
$Ret(-12,-2)$		0.100	0.078	0.071		0.026	-0.000	-0.047
		(0.125)	(0.120)	(0.107)		(0.112)	(0.110)	(0.104)
Idiosyncratic volatility		-0.510	-0.608**	-0.537**		-0.446**	-0.554***	-0.565***
		(0.311)	(0.289)	(0.266)		(0.192)	(0.179)	(0.177)
SUE		-0.021	0.015	0.009		0.054	0.051	0.044
		(0.092)	(0.090)	(0.082)		(0.038)	(0.037)	(0.036)
Patents/Assets			0.253*	0.106			0.064	0.029
			(0.149)	(0.117)			(0.064)	(0.056)
R&D/Market equity			0.120	0.135			0.227***	0.207***
			(0.100)	(0.087)			(0.062)	(0.059)
Innovation originality			-0.023	0.054			0.022	0.023
			(0.042)	(0.039)			(0.027)	(0.027)
Citations-based innovative efficiency			0.147	0.105			0.099**	0.110***
			(0.116)	(0.095)			(0.039)	(0.037)
Patents-based innovative efficiency			-0.113	-0.067			-0.100**	-0.098**
			(0.099)	(0.094)			(0.041)	(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
R2	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; otherwise it is the seasonally differenced quarterly earnings before extraordinary items from the 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.24. 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)	(0.040)	(0.042)	(0.024)	(0.054)	(0.062)
Middle	1.009***	-0.099***	-0.195***	-0.073***	0.121***	0.231***
	(0.022)	(0.029)	(0.032)	(0.025)	(0.033)	(0.066)
High	1.018***	-0.001	-0.121***	-0.107***	0.151***	0.540***
	(0.024)	(0.047)	(0.041)	(0.030)	(0.051)	(0.065)
Low-High	-0.059*	-0.047	-0.167**	0.118***	-0.153**	-0.659***
	(0.034)	(0.063)	(0.067)	(0.045)	(0.061)	(0.099)

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***
	(0.025)	(0.040)	(0.067)	(0.056)	(0.065)
Middle	1.026***	-0.113***	0.005	-0.032	0.244***
	(0.022)	(0.027)	(0.063)	(0.037)	(0.045)
High	1.013***	-0.036	0.405***	-0.031	0.104
	(0.024)	(0.051)	(0.074)	(0.050)	(0.076)
Low-High	-0.034	-0.018	-0.873***	-0.039	0.150
	(0.031)	(0.080)	(0.122)	(0.074)	(0.110)

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

	MKT	SMB	HML^{INT}	UMD
Low	0.997***	0.006	-0.287***	0.015
	(0.025)	(0.032)	(0.031)	(0.031)
Middle	0.979***	-0.116***	0.005	-0.045*
	(0.030)	(0.022)	(0.032)	(0.027)
High	0.935***	-0.053	0.197***	-0.068*
	(0.030)	(0.039)	(0.059)	(0.040)
Low-High	0.062	0.059	-0.484***	0.083
	(0.039)	(0.058)	(0.073)	(0.063)

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***
	(0.026)	(0.043)	(0.041)	(0.027)	(0.057)	(0.064)
Middle	1.010***	-0.068**	-0.092*	-0.060**	0.118***	0.125
	(0.023)	(0.032)	(0.054)	(0.029)	(0.037)	(0.084)
High	1.021***	0.021	-0.076	-0.101***	0.158***	0.489***
	(0.025)	(0.046)	(0.051)	(0.033)	(0.058)	(0.076)
Low-High	-0.053	-0.015	-0.113*	0.125***	-0.139**	-0.723***
	(0.035)	(0.062)	(0.068)	(0.048)	(0.071)	(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).