Nature Dependence, Economic Value, and Extinction Risk: Evidence from Biotech Innovations*

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Abstract

This paper examines how nature dependence translates into economic value in the context of biotech innovations. We identify biotech patents as those involving the application of science to living organisms, and document that biotech patenting activities span across industries. Our most conservative estimate indicates that biotech patents are $639,000 more valuable than other granted patents, which is also reflected in firm level valuation and cash flow metrics. Exploiting a shock to the recognition of extinction risk of species in a patent, we show that constrained firms have lower valuation, cash flows, and capital expenditures. Overall, our results suggest that while nature dependence via biotechnology is valuable, the recognition of extinction risk can have significant implications for firm value.

Keywords: Nature dependence, biotech innovation, firm value, biodiversity finance, extinction risk

JEL codes: G32, G31, Q57

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1 Introduction

Policymakers and investors increasingly recognize that firms' dependence on nature can give rise to material financial risks and opportunities. While a number of recent studies show that investors have begun demanding a compensation for risks associated with nature dependence and biodiversity loss (Coqueret et al., 2025; Garel et al., 2024), survey results reveal that—surprisingly—only a minority of companies believe that these risks will affect firm value (Gjerde et al., 2025). Indeed, even though all firms ultimately rely on nature, the mechanisms through which nature dependence directly affect cash flows remain poorly understood (TNFD, 2023; Gjerde et al., 2025).

One setting where a firm's production and nature are directly linked is biotechnology. Biotechnology offers firms a way to capitalize on nature and monetize science across sectors such as agriculture, energy, and medicine, yet most companies in this domain remain unprofitable outside a handful of pharmaceutical outliers (see, for example, Pisano, 2006; Purcell, 1999; Thakor et al., 2017; Ernst & Young, 2024; Senior, 2024). The rapid decline in global biodiversity further complicates this value proposition, as technologies that depend on vulnerable biological inputs may face premature write-downs and become stranded assets.

In this paper, we assess the economic value of nature dependence in the context of biotech innovations, and examine how extinction risk affects firm value. First, we apply and adapt the Organisation for Economic Co-operation and Development's (OECD) definition of biotech (Friedrichs and van Beuzekom, 2018)—technology that involves the application of science and knowledge to living organisms—to patent abstracts and the Cooperative Patent Classification (CPC) codes, and identify biotech patents granted by the United States Patent and Trademark Office (US PTO).[1] Second, we examine the value and characteristics of biotech patents, and validate these attributes using firm level valuation and cash flow metrics. Finally, we use the recognition of extinction risk in the International Union for Conservation of Nature's (IUCN) Red List as a natural

[1] Friedrichs and van Beuzekom (2018) define biotechnology as "*the application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or non-living materials for the production of knowledge, goods and services* (p. 8)."

experiment, and assess the valuation implications of biodiversity loss for firms with innovations that capitalize on the relevant species.

Our findings make three distinct contributions. First, we identify 65,798 biotech patents granted to publicly traded firms in the United States in between 1980 and 2019. We document that biotech patenting activities span across industries and patent categories, consistent with the notion that biotechnology cuts across beyond sector boundaries. Second, we highlight the incremental value of biotech among the set of granted patents. Our most conservative estimate indicates that biotech patents are $191,000 (1982 dollars, approximately $639,000 in 2024 dollars) more valuable than non-biotech patents.[2] This higher value is reflected at the firm level, with firms that own more biotech patents being more valuable and profitable, consistent with the monetization appeal of biotech. Third, exploiting the variation in the recognition of species-level extinction risk, we find that only the valuation and profitability of operationally or financially constrained firms are significantly negatively affected. These constraints also limit the scope of adaptive strategies, presenting barriers to transition away from biodiversity risk. Collectively, our findings show that while biotech provides companies a pathway to capitalize on nature and monetize science, biodiversity risk can significantly affect firm value if there are barriers to transition.

To link corporate patenting activities to biological information, we combine patent data from Orbis Intellectual Property with species information from Global Biodiversity Information Facility (GBIF) and biological information from PubChem. We designate a patent as a biotech patent if any one of the following conditions is met: (1) a gene, protein, cell or species is identified in the patent abstract, and (2) the cooperative classification code of the patent belongs to the OECD's definition of biotechnology (Friedrichs and van Beuzekom, 2018). We identify 40,472 patents at the United States Patent and Trademark Office (USPTO) that mention a gene, protein, cell or species. Using the list of CPC codes in Friedrichs and van Beuzekom (2018), we identify 35,516 patents

[2]Kogan et al. (2017) provide inflation-adjusted value of patents by deflating nominal values to 1982 prices. We convert 1982 prices into 2024 prices by adjusting for the Consumer Price Index.

that fall under OECD's definition of biotechnology.[3] We link patent-level information to annual financial data from Compustat and monthly stock returns from CRSP. We restrict our sample to firms in the United States with at least one patent. Our sample period begins in 1980, where patent coverage is better, and ends in 2019, to allow for the time lag in between patent applications and grants, and to alleviate truncation bias (Lerner and Seru, 2022).

We begin our empirical analyses by examining the economic value of biotech patents, using the market-based patent values estimated in Kogan et al. (2017). Our estimates from fixed effects Poisson regressions indicate that the conditional mean of the value of biotech patents is \$1.084M to \$1.165M (1982 dollars, approximately \$3.63M to \$3.90M in 2024 dollars) higher than other patents. Our baseline estimates include industry-grant year fixed effects, which address the concern that blockbuster patents are concentrated in certain industries, and that patent values may be affected by overall market valuation in a given year. In more stringent specifications, we include firm-year fixed effects, narrowing the comparison to patents granted to the same firm in the same year. Under these specifications, we find that the conditional mean of the value of biotech patents is \$191,000 to \$200,000 (1982 dollars, approximately \$639,000 to \$669,000 in 2024 dollars) higher than other patents.

We hypothesize that the higher economic value of biotech patents reflects higher innovation rents, and provide three pieces of evidence in support of this hypothesis. First, using the measure of scientific value in Kelly et al. (2021), we show that biotech patents are more novel and impactful. Second, we show that biotech are more likely to be commercialized, reflecting the potential for monetization. Third, we show that biotech patents are less likely to be litigated. We interpret this as evidence that these patents are more excludable, i.e. patent holders are better able to prevent unauthorized use or imitation. Together, these results are consistent with that biotech patents provide holders with a competitive advantage in monetizing scientific innovations, and therefore are more valuable.

[3]These two criteria are not mutually exclusive, and some patents fall under both categories. We defer the discussion till Section 2.2.

Next, we perform a validation exercise to examine whether the patent level results on valuation and commercialization are reflected at the firm level. Using the sample of patenting firms in the United States, we find economically large effects on both valuation and profitability. A one standard deviation increase in the log of one plus the number of biotech patent stock is associated with a 0.097–0.106 standard deviation higher valuation, as measured by the log of market-to-book ratio, and a 0.016–0.027 standard deviation higher profitability, as measured by the operating profit-to-asset ratio.

After establishing the valuation and cash flow effects of biotech patenting activities, we assess the economic significance of biodiversity risks. We focus on the recognition of extinction risk, and use updates to the IUCN Red List of Threatened Species as a natural experiment. Employing a stacked difference-in-differences methodology with a [-3,+3] window, we find insignificant effects on firm valuation and profitability among treated firms, defined as firms with a patent that mentions a species newly identified to be vulnerable or endangered in the Red List. However, using a triple difference methodology, we find treated firms that are more operationally constrained, as proxied by the number of patents, or financially constrained, as proxied by market leverage, have statistically significantly lower valuation and profitability. The economic magnitudes are large: Depending on the measures of constraints, valuation as measured by the log of market-to-book ratio is 1.04–1.23 standard deviations lower, and profitability as measured by the EBIT-to-assets ratio is 0.28–0.35 standard deviations lower. Our results indicate that the recognition of extinction risk in one species can have significant value implications for a firm that depends on the species.

We further examine whether firms transition away from extinction risk via corporate investment and innovation. Similar to the valuation and profitability results, we find insignificant average effects on capital expenditures and research and development (R&D) expenses. However, using the same set of proxies for operational and financial constraints, we find that treated firms that are more constrained lower capital expenditures. We find much weaker effects on R&D expenses.

Collectively, we interpret that extinction risk exerts a twofold effect on constrained

firms. First, the valuation and profitability of these firms are negatively affected. Second, these firms have to ration resources in their adaptation plan, significantly lowering capital expenditures. The key implication of these results is that while extinction risk in the context of corporate patenting may not equally affect all firms, its effects on constrained firms are significant as these firms have limited resources to transition away from existing technologies.

Our findings contribute to the nascent literature on biodiversity finance. Several papers examine the role of private capital and blended financing structures in biodiversity conservation (Flammer et al., 2025; Karolyi and la Puente, 2023), highlighting the need to understand the risk-return trade-offs and conservation impact. Coqueret et al. (2025). Garel et al. (2024), and Giglio et al. (2023) explore the pricing of biodiversity-related risks and opportunities in equities, whereas Hoepner et al. (2023), Chen et al. (2023), and Rizzi (2022) study the bond markets. Garel et al. (2025) introduce a firm-level measure of nature dependence and therefore path the way towards better identifying nature risks. Our findings relate to this literature in three ways. First, we provide a novel measure of nature dependence of firms based on patents, and document the widespread use of biotech innovations. Second, our valuation analyses provide valuation estimates on innovation activities that depend on nature and natural capital. Third, we show that while innovation-specific biodiversity risk is likely diversifiable, firms that are more operationally or financially constrained are significantly negatively affected by the recognition of extinction risk, and face greater obstacles in the transition process.

Our paper contributes to the literature on the role of innovation in the transition to a sustainable economy. Most papers focus on green innovation. While there is no single definition of green innovation, green innovation is typically considered to be a form of innovation that facilitates the transition or adaption towards net-zero. One stream of the literature assesses the role of green innovation on real outcomes, such as carbon emissions (Bolton et al., 2024; Hege et al., 2025; Leippold and Yu, 2023). Another stream of literature examine the value implications of green innovation with mixed conclusions (Andriosopoulos et al., 2022; Reza and Wu, 2024; Briere et al., 2025).

In contrast to these studies, we are the first to shift the focus from green innovation to nature-dependent innovation. Specifically, we quantify the valuation implications of biotech patents in the context of the biodiversity crisis. We find that biotech patents are on average more valuable than non-biotech patents. Consistent with biotech patents having greater monetizing potential, we find that biotech patents are more novel, more likely to be commercialized, and less likely to be litigated.

Finally, our findings also relate to the literature on the barriers to adaptation. While the literature on adaptation to biodiversity risk is still in its early stages, considerable attention has been given to studying barriers to adaptation in the climate economics literature (see, for example, Fankhauser, 2017; Mendelsohn, 2000, 2012; Moser and Ekstrom, 2010). As summarized in Biesbroek et al. (2013), most barriers to adaptation are not specific to climate change. Burton (2004) and Smith et al. (2011) examine the role of country level resource and funding constraints in leading to an adaptation deficit. Custódio et al. (2025) provide firm level evidence that operational and financial constraints amplify the impact of rising temperatures on both firm profitability and adaptation. We find that in response to the recognition of extinction risk, firms that are operationally or financially constrained lower capital investments, and with much weaker effects, R&D. These results dovetail nicely with the findings in Custódio et al. (2025).

2 Research Design

2.1 Data Sources

Our patent level sample consists of patents granted to firms in the United States. The sample period begins in 1980, where patent coverage is better, and ends in 2019, to allow for the time lag between patent applications and grants and thus alleviate truncation bias (Lerner and Seru, 2022). We describe our primary data sources below.

2.1.1 Patent data

We obtain patent data from the United States Patent and Trademark Office (USPTO) from Orbis Intellectual Property. This data provides a comprehensive coverage of patent filings and information such as application dates, grant dates, CPC codes, and patent abstracts.[4] Importantly, Orbis Intellectual Property provides information on corporate ownership of patents. We obtain patent values from Kogan et al. (2017), and information on scientific breakthroughs from Kelly et al. (2021).

2.1.2 Biological and biotechnology information

We identify biotech patents using a two-pronged approach. We designate a patent as a biotech patent if any one of the following conditions is met: (1) a gene, protein, cell or species is identified in the patent abstract, and (2) the CPC code of the patent belongs to the OECD's definition of biotechnology (Friedrichs and van Beuzekom, 2018).

Biological information

We obtain information on genes, cells, and proteins from PubChem. PubChem is an open chemistry database at the United States National Institute of Health. PubChem provides information on chemical structures, chemical and physical properties, biological activities, etc, with identifiers that can be used to link across various external databases.

Taxonomic information (species names, description, and classification) is sourced from the Global Biodiversity Information Facility (GBIF) Backbone Taxonomy. The GBIF is an international network and data infrastructure that provides access to data about all types of life on Earth. The GBIF Backbone Taxonomy is a synthetic management classification that integrates name-based information from various resources, providing means to crosswalk names from these sources.

We retrieve the list of plants, fungi, and animal species that are at risk of extinction from the International Union for Conservation of Nature (IUCN) Red List of Threatened

[4]We supplement any missing abstracts with information on patent abstracts from Patentsview.

Species. The IUCN is a membership union of governmental and civil society organizations that advance sustainable development and nature conservation. The Red List of Threatened Species is the most comprehensive information source on the global extinction risk status of animal, fungus and plant species (Rodrigues et al., 2006; Betts et al., 2020; IUCN, 2024).

We link biological information from PubChem, taxonomy data from GBIF, and species risk assessment data from IUCN via the scientific names of species. We then search for genes, cells, proteins, and scientific species names in patent abstracts. We further verify all biotech patents using a large language model (ChatGPT), which we use to assess the contextual relevance of biological terms and to identify false positives A subset of the machine-verified biotech patents is then manually verified to ensure accuracy. We report our large language model instructions in Appendix C.

Biotechnology information

We obtain the list of CPC codes relevant to biotechnology from Friedrichs and van Beuzekom (2018). Friedrichs and van Beuzekom (2018) define biotechnology as "*the application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or non-living materials for the production of knowledge, goods and services* (p. 8)." If one of the CPC codes of a patent falls under the list in Friedrichs and van Beuzekom (2018), we classify the patent as a biotech patent.

2.1.3 Financial data

Annual financial data is from Compustat, monthly stock returns data from CRSP, and risk factors from Ken French's website. We drop firms (1) headquartered outside of the United States, (2) with sales or total assets below $5 million, or (3) without a patent.

2.2 Descriptive statistics

Table 1 reports the industry and CPC code distributions of biotech patents at the two-digit NAICS code level and CPC main section level. Using our two-pronged approach, we

identify 65,798 biotech patents owned by 2,637 Compustat firms. As shown in Panel A, while the majority of biotech patents are owned by firms in the manufacturing industry (NAICS: in 31-33), it is noteworthy that biotech patenting activities span across multiple industries. This lends support to our bottom-up approach that identifies biotech firms through patenting activities. As shown in Panel B, biotech patents span across all patent categories, with the majority in chemistry and metallurgy section. Table A2 in the online appendix reports the breakdown of biotech patents identified via different approaches.[5] Table A3 reports additional summary statistics of variables used in the robustness checks. Table B1 in the internet appendix provides some examples of the biotech patents identified.

Figure 1 plots the number and proportion of biotech patent grants over time. In Panel A, the sample covers the full patent sample. In Panel B, the sample covers patents owned by Compustat firms. There are two noteworthy patterns. First, while there is a general uptrend, there is some variability in the growth rate in the number of biotech patent applications. In particular, the spike in biotech patent applications around 1998 likely reflects the change from a 17-year patent term to a 20-year patent term in 1995 (Adelman and DeAngelis, 2006). Second, the number and proportion of biotech patents granted to publicly listed firms have been declining over time. In the online appendix, Figures A1 and A2 graph the time trends for GBIF/PubChem patents (i.e. patents that mention at least one species in GBIF Backbone taxonomy or at least one gene, protein or cell in PubChem) and OECD patents (patents with CPC codes falling under OECD's definition in Friedrichs and van Beuzekom (2018)) separately. The patterns are consistent with Figure 1.

Table 2 reports the summary statistics of the variables used in the main analyses. Table A1 in the online appendix provides detailed variable definitions. Our core analyses are at the single-day grant patent level, and the firm-year level. We defer the description of the sample construction process to later sections. Panel A reports summary statistics

[5]Among these patents, 6,889 mention at least one species based on the GBIF Backbone Taxonomy; 35,139 mention at least one PubChem gene, protein or cell; 35,516 have a CPC code that falls under OECD's classification of biotech.

for the patent level sample. Within the single-day grant patent sample, 5.2% of patents are identified as biotech patents. Panel B reports the summary statistics for the firm-year level sample, where the sample consists of patenting firms. Panel C reports summary statistics in the firm-year level stacked difference-in-differences sample.

Figure 2 graphs the histograms of the log value of biotech and non-biotech patents, based on Kogan et al. (2017). The log values of both biotech and non-biotech patents follow a bell-shaped distribution, with heavier tails on both ends. Remarkably, biotech patents have a heavier mass on the right, indicating that relative to non-biotech patents, there is a higher proportion of biotech patents that are more valuable.

3 Results

We begin our empirical analyses by examining the value and characteristics of biotech patents. Next, we examine whether these valuation effects are reflected at the firm and portfolio levels. Finally, we use changes in the IUCN Red List as a natural experiment to assess the relevance of extinction risk.

3.1 Value of biotech innovations

3.1.1 Patent level results

Patent value

We begin our empirical analyses by examining the value of biotech patents relative to other patents, conditional on the sample of patents that are granted. As patent values are bounded from zero and skewed to the right, we employ the following fixed effects Poisson model (Cohn et al., 2022):

$$\mathbb{E}[Patent\ Value_p|\mathbf{x}] = exp(\beta_1 Biotech\ Patent_p + \alpha_{j,t}) \tag{1}$$

where $Patent\ Value_p$ is the private economic value of patent p, as estimated in Kogan et al. (2017). $Patent\ Value$ is inflation-adjusted and reflects the real value in 1982 dollars

(in millions). *Biotech Patent*$_p$ is an indicator that is equal to one if patent p is a biotech patent, as defined in Section 2.1.2. $\alpha_{j,t}$ is the industry-grant year fixed effect, where industry is defined at the six-digit NAICS code level. The granularity of the industry-year fixed effects helps alleviate concerns over the possibility that β_1 is confounded by systematic differences in patent values across industries or capital market conditions. In the most stringent specification, we include firm-year fixed effects to absorb time-varying unobserved heterogeneity at the firm level. Standard errors are double-clustered at the industry and grant year levels. To estimate the differences between biotech and non-biotech patents, we exclude patents that are granted to the same firm on the same grant day.[6]

Table 3 reports the results. In column (1), we only include industry-year fixed effects. In column (2), we further include CPC code fixed effects, where CPC codes are defined at the section level. In both specifications, the coefficient of *Biotech Patent* is statistically significant at conventional levels, though it drops to the 10% level after the inclusion of CPC code fixed effects. Based on these estimates, the predicted conditional mean value of a bitoech patent is \$1.084M to \$1.165M (1982 dollars, approximately \$3.63M to \$3.90M in 2024 dollars) higher than a non-biotech patent.

A potential concern is that β_1 in columns (1) and (2) capture patent level differences as well as firm level differences. To obtain a narrower comparison, we include firm-year fixed effects, where the coefficient of *Biotech Patent* captures the difference between biotech and non-biotech patents granted to the same firm in the same year. In column (3), we only include firm-year fixed effects, and in column (4), we further include CPC code fixed effects. Relative to columns (1) and (2), the coefficient of *Biotech Patent* shrinks to 0.009–0.010, but is statistically significant at conventional levels. Based on these estimates, for a firm that files both biotech and non-biotech patents, the predicted conditional mean value of a biotech patent is \$191,000–\$200,000 (1982 dollars, approximately \$639,000–\$669,000 in 2024 dollars) higher than a non-biotech patent.

[6]For multiple patents granted to the same firm on a grant date, Kogan et al. (2017) split the value equally across all patents, which mechanically eliminates differences between the values of biotech and non-biotech patents.

Another potential concern that the higher value of biotech patents is driven only by patents filed by pharmaceutical companies. Table 4 addresses this concern by presenting results from sample splits. Columns (1) and (2) examine the value of biotech patents granted to non-pharmaceutical firms (i.e. excluding firms with SIC code: 2834 or NAICS code: 3254). Columns (3) and (4) examine the value of pharmaceutical biotech patents granted to pharmaceutical firms only. In all cases, we find that biotech patents are statistically significantly more valuable non-biotech patents, translating into a $282,000–$375,000 (1982 dollars, approximately $943,000–$1.255M) difference depending on the empirical specification.

These findings indicate that biotech patents have a higher economic value than other non-biotech patents. Our less stringent estimates, which control for sectoral differences and overall market valuation effects via industry-year fixed effects, show that biotech patents are approximately $1M (1982 dollars, approximately $3.35M in 2024 dollars) more valuable. Our more stringent estimates, which control for unobserved, time-varying firm characteristics, show that biotech patents are approximately $200,000 (1982 dollars, approximately $669,000 in 2024 dollars) more valuable. The incremental value associated with biotechnology is robust to focusing on non-pharmaceutical companies only, as well as pharmaceutical companies only. Overall, our results indicate that in the context of innovation, capitalizing on biocellular and biomolecular processes is associated with incremental economic value.

Patent characteristics

The higher economic value of biotech patents suggests that these patents provide the patenting firms with a competitive advantage to earn higher innovation rents (McGrath et al., 1996). To test the hypothesis that biotech patents provide the patenting firms with a more distinct competitive advantage, we examine the scientific value and monetizability of these patents.

To measure a patent's scientific value, we use 5-*year Importance*, a measure of scientific value and technological breakthrough based on textual analysis of the patent

document in relation to previous work (novelty) and subsequent work (impact) (Kelly et al., 2021). We expect biotech innovations to have higher scientific value, providing the patenting firm a technical advantage.

To measure the degree of monetizability, we look at two characteristics. The first characteristic is *Commercialization*, an indicator variable that is equal to one if the patent abstract clearly indicates the intention for commercialization. We construct this variable using a large language model to analyze patent abstracts. Panel C of Table C1 in the online appendix provides the full specification of the settings. We expect biotech innovations to be more likely to have the intention to be commercialized, providing the patenting firm a product market advantage.

The second characteristic that measures monetizability is *Litigated*, an indicator variable that is equal to one if the patent has been litigated against. We hypothesize that innovation rent from biotech patents are more excludable and less likely to be dissipated away via patent litigation (see, for example, Bessen and Meurer, 2006; Cohen et al., 2019; Lanjouw and Schankerman, 2001). As such, we expect biotech patents to be less litigated.

Unlike patent values, these patent characteristics are not count-like variables. As a result, we employ the following fixed effects model:

$$Patent\ Characteristic_p = \beta_1 Biotech\ Patent_p + \alpha_{j,t} + \varepsilon_p \tag{2}$$

where $Patent\ Characteristic_p$ is a variable that captures a characteristic of patent p. Similar to Equation (1), we include industry-year fixed effects, where industry is defined at the 6-digit NAICS code level, and double-cluster the standard errors at the industry and year levels.

Table 5 reports the results. In Panel A, the dependent variable is 5-*year Importance*. The coefficient of *Biotech Patent* ranges from 0.031 to 0.062, and is statistically significant at the 1% level across specifications. This means that on average, biotech patents have a 0.13–0.27 standard deviation higher 5-*year Importance* relative to non-biotech

patents.

As a robustness check, Table A4 in the online appendix provides alternative measures of scientific value and technological breakthrough: 10-*year Importance*, and breakthrough patent indicators based on whether a patent's 5- or 10-*year Importance* is in the top decile. The results remain qualitatively similar.

In Panel B of Table 5, the dependent variable is *Commercialization*. The coefficient of *Biotech Patent* ranges from 0.008 to 0.036, and is statistically significant in all specifications, except for the one with only industry-year fixed effect in column (1). With the inclusion of CPC fixed effects in column (2), the coefficient becomes statistically significant and increases in size, which suggests that after controlling for unobserved heterogeneity at the patent type level, biotech patents are more likely to be commercialized.

In Panel C of Table 5, the dependent variable is *Litigated*. The coefficient of *Biotech Patent* ranges from -0.005 to -0.015, and is statistically significant at conventional levels. This means that on average, biotech patents have a 0.04–0.11 standard deviation lower likelihood to be litigated relative to non-biotech patents.

As an additional set of analyses, Table A5 in the online appendix examines whether biotech patents are more likely to be process innovations that lower production costs, as identified by Bena and Simintzi (2023). The lack of consistently significant results indicates that biotech patents are not statistically more likely to be inventions that apply to production techniques.

Our patent level findings indicate that biotech patents exhibit characteristics typically associated with greater competitive advantage. They appear more novel and impactful, and are associated with greater monetization potential, as reflected in a stronger commercialization focus and lower litigation risk. These characteristics provide the patenting firms with a technical and product market advantage, and monetization potential, translating into a higher private economic value.

3.1.2 Firm level results

Next, we examine whether the higher value and monetization of biotech patents is reflected at the firm level. In this set of descriptive analyses, we estimate the following fixed effects model:

$$\begin{aligned} y_{i,t} =& \beta_1 Log(1 + Biotech\ Patent\ Stock_{i,t-1}) \\ &+ \beta_2 Log(1 + Non\text{-}biotech\ Patent\ Stock_{i,t-1}) \\ &+ \gamma' \mathbf{x} + \alpha_i + \alpha_{j,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $y_{i,t}$ is firm i's valuation or profitability variables in year t. $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$ is the log of one plus the number of biotech patents firm i owns in year $t-1$. We interpret this variable as a score that measures the extent of a firm's biotech patenting activities. To control for other innovative activities, we add $Log(1 + Non\text{-}biotech\ Patent\ Stock_{i,t-1})$, log of one plus the number of non-biotech patents firm i owns in year $t-1$. $\mathbf{x}$ is a vector of firm-level control variables, including a firm's log assets, Tobin's Q, leverage, cash-to-asset ratio, and PPE-to-assets ratio. α_i and $\alpha_{j,t}$ are firm fixed effect and industry-year fixed effect, respectively. Industry is defined at the six-digit NAICS code level. Standard errors are clustered at the firm level. To capture the difference between biotech and non-biotech innovations, we restrict the sample to patent-filing firms only.

Table 6 reports the results. In columns (1) and (2), the dependent variable is the log of $Log(Market\text{-}to\text{-}Book)$, the market-to-book ratio of a company's equity. The coefficient of $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$ ranges from 0.093 to 0.101, and is positive and statistically significant at the 1% level. A one standard deviation increase in $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$ is associated with a 0.097-0.106 standard deviation higher $Log(Market\text{-}to\text{-}Book)$. In columns (3) and (4), the dependent variable is $EBIT/Assets$, the operating profit-to-assets ratio. The coefficient of $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$ ranges from 0.016 to 0.027, and is positive and statistically significant at the 1% level. A one standard deviation increase in $Log(1+Biotech\ Patent\ Stock_{i,t-1})$

is associated with a 0.081–0.137 standard deviation higher $EBIT/Assets$.

While this analysis does not yield a causal interpretation, there are two noteworthy implications: First, the higher value of biotech patents is reflected at the firm level, with firms that have more biotech patents having higher valuation and profitability. Second, while prior evidence indicates that biotech companies are mostly unprofitable (see, for example, Pisano, 2006; Purcell, 1999; Thakor et al., 2017; Ernst & Young, 2024; Senior, 2024), we reveal a positive association at the intensive margin by identifying biotech firms via biotech patenting activities.

As robustness checks, Table A6 the results without pharmaceutical companies. In light of prior studies that show that the financial performance of biotech firms are driven by pharmaceutical companies (see, for example Pisano, 2006; Thakor et al., 2017), we re-run Table 6 without pharmaceutical companies (SIC code: 2834 or NAICS code: 3254). On valuation, we find a similar coefficient of $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$ (0.094–0.104), which is significant at the 1% level across specifications. In contrast, on profitability, we find a smaller coefficient (0.009–0.012), which remains statistically significant at the 5% and 10% levels depending on the specification.

Table A7 in the online appendix reports alternative specifications. In columns (1) and (2), we do not control for $Log(1 + Non\text{-}biotech\ Patent\ Stock_{i,t-1})$, which does not have a material effect on the coefficient of $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$. In columns (3)–(6), we use the log of Tobin's Q (i.e. the market-to-book ratio of assets without taking intangible capital into account) as an alternative measure of valuation. In columns (3)–(4), we exclude Tobin's Q as a control variable to avoid biasing the coefficient estimates by including the lag of the dependent variable. In columns (5)–(6), we include Tobin's Q as a control variable to facilitate comparison to our preferred specifications. In columns (7) and (8), we use the net income-to-assets ratio as an alternative measure of profitability. The results in these alternative specifications are qualitatively similar to those in Table 6.

Table A8 reports the results with alternative dependent variables, where we replace $Log(1 + Biotech\ Patent\ Stock_{i,t-1})$ and $Log(1+ Non\text{-}biotech\ Patent\ Stock_{i,t-1})$ with

the ratio of biotech patent stock, the log of all patent stock, and their interaction. The interaction term provides another way to capture the extent of a firm's biotech patenting activities. The coefficient is positive and statistically significant at the 1% to 5% levels, depending on fixed effects, which is consistent with our baseline results.

As an additional analysis, we assess whether the value of biotech patents are fully incorporated into stock prices. The prior literature has documented instances where market participants may fail to fully incorporate the value of intangible assets into stock prices, resulting in returns in excess of priced risk factors (see, for example, Edmans, 2011; Khan et al., 2016). To examine whether the value of biotech patents are fully incorporated into stock prices, we test for the existence of abnormal returns in portfolios. We construct value-weighted and equal-weighted portfolios of firms that own a biotech patent, where the portfolios are rebalanced monthly to incorporate patent grants only a monthly interval. As we are testing the joint hypothesis that the asset pricing model is correct and that market prices reflect all available information, we test four commonly used factor models, and examine whether the abnormal return is consistently statistically significant. Table A9 in the online appendix shows that in all instances, α is statistically insignificant, suggesting that neither a value-weighted nor a equally weighted biotech portfolio generates a return in excess of exposure to priced risk factors.

3.2 Valuation implications of biodiversity risk

3.2.1 Hypothesis development

Our preceding analyses suggest that successful biotech innovations are more valuable and monetizable, the effects of which are reflected at the firm level. However, biotech firms, while capitalizing on biological processes, may also be exposed to biodiversity risks due to their reliance on specific biological inputs or processes (TNFD, 2023). Richardson et al. (2023) show that the current rate of genetic diversity loss has far exceeded the safe operating space, estimated to be at least tens to hundreds of times higher than the average rate over the past 10 million years. Extinction risk thus presents a major threat to the ecosystem, and has gained increasing public attention.

For the following analysis, we assess the value implications of the species-level extinction risk. We hypothesize that biotech firms that rely on vulnerable biological inputs and processes may suffer from valuation losses when the relevant biological inputs become endangered. For biotech firms that use species-specific production technologies, the potential loss of access to critical biological inputs may severely disruption production. Barrot and Sauvagnat (2016) highlight the importance of input specificity by showing that, in the context of production networks, suppliers impose substantial output losses on customers especially if the suppliers produce specific inputs. In addition, policy and product market risks may impose significant impact on the value of biotech. For example, policymakers may introduce regulations, such as trade restrictions, to create positive and mitigate negative impacts on nature. Market dynamics and consumer preferences may also change in light of a company's reliance and impact on nature. In short, we hypothesize that the valuation of firms will be negatively affected when a patent-relevant species is recognized to be endangered.

While biodiversity risk may be financially material, Coqueret et al. (2025) and Garel et al. (2024) show that investors only begin pricing biodiversity risk in 2021, indicating that attention to biodiversity risk over our sample period may not be economically significant. As such, whether biodiversity risk—extinction risk in particular—is financially material in the context of corporate patenting activities is an empirical question.

3.2.2 Empirical design

We exploit the IUCN Red List as a natural experiment to assess the financial consequences of the recognition of extinction risk. The IUCN Red List Categories indicate how close a species is to becoming extinct (IUCN, 2024), which raises the awareness of the conservation status of a species. For species that are evaluated, IUCN assigns a species to one of the following seven categories, in ascending order of extinction risk: (1) least concerned, (2) near threatened, (3) vulnerable, (4) endangered, (5) critically endangered, (6) extinct in the wild, and (7) extinct. Van Huynh (2023) finds that Google searches for a given species increase significantly following the designation of a higher

IUCN Red List risk category, indicating that updates in the Red List draws significant public attention. Table B2 in the online appendix provides an example of a patent that mentions a threatened species in our sample.

There are a number of possible reasons why firm valuations may affected when a patent-relevant species is listed on the IUCN Red List. First, species that are exposed to extinction risk are likely to be subject to trade regulations. Challender et al. (2023) find that 59% of species that are threatened by international trade are on the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) appendices, which prohibits (Appendix I) or controls (Appendices II and III) commercial trade of specimens. In other words, being listed on the Red List may indicate higher potential compliance costs in the future. Second, the Red List may shift patterns of consumption via a labeling effect. For example. Teisl et al. (2002) and Hallstein and Villas-Boas (2013) find that sustainability or eco-labels can have significant effects on sales of seafood products. If the Red List deters consumers from using relevant products, then cash flows of these firms will be negatively affected.

We employ the following difference-in-differences model to examine the average effects:

$$y_{i,t} = \beta_1 TREAT_{k,i} \times POST_{k,t} + \alpha_{k,i} + \alpha_{k,j,t} + \varepsilon_{k,i,t} \tag{4}$$

where $y_{i,t}$ is firm i's valuation or profitability variables in year t. In the main analysis, we use the log of the market-to-book ratio as a measure of valuation, and the operating profit-to-assets ratio as a measure of profitability. $TREAT_{k,i}$ is an indicator that is equal to one if firm i has a patent that uses a species newly identified to be near threatened (category (2) in the above) or threatened (categories (3)–(7)) in the k^{th} edition of IUCN Red List. In our sample, the relevant species in the affected patents are listed as either near threatened (category (2)) or endangered (category (4)). $POST_{k,t}$ is an indicator that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. The individual coefficients of $TREAT_{k,t}$ and $POST_{k,t}$ are absorbed by

the edition-firm ($\alpha_{k,i}$) and edition-industry-year ($\alpha_{k,j,t}$) fixed effects, respectively. As the treatment is assigned to the firm, we cluster standard errors at the firm level (Abadie et al., 2023).

To ensure a valid comparison between treated and control firms, we add two additional restrictions to the firm-year level sample. First, for each IUCN edition, we restrict control firms to be in the same industry group (defined as four-digit SIC codes or six-digit NAICS codes) as the treated firms. Second, we require each firm to be in the sample throughout a [-1,+1] window around each IUCN edition. The resulting sample is small relative to the preceding analyses, with 1,182 observations in total. As a result of these sample restrictions, the parameter of interest, β_1, captures the average treatment effect of the recognition of extinction risk by comparing treated biotech firms that have a species mentioned in a new edition of the IUCN Red List to control firms that have biotech patents but are not affected by that particular edition of the Red List.

3.2.3 Extinction risk and valuation

Table 7 reports the valuation implications of extinction risk. Panel A shows the average effects. In column (1), we examine the effect on valuation. The coefficient of $TREAT \times POST$ is 0.019, but is not statistically significant at conventional levels. In column (2), we examine the effect on profitability. The coefficient is -0.039, which is also not statistically significant at conventional levels. These results suggest that an increase in extinction risk is not significantly associated with lower valuation and profitability. Figure 3 provides the relevant coefficient plots, which indicates that there are no statistically significant pre-trends between treated and control firms prior to the treatment.

These null average effects indicate that innovation-specific extinction risk is not material on average. However, firms with binding constraints may not be able to diversify away from these risks, and will be negatively affected by the heightened recognition of extinction risk. As such, we incorporate the role of constraints, and hypothesize that *constrained* firms exposed to greater extinction risk will have a lower valuation and lower profitability. To examine the role of constraints empirically, we employ the

following triple difference model:

$$\begin{aligned} y_{i,t} =& \beta_1 TREAT_{k,i} \times POST_{k,t} \times CONSTRAINT_{k,i} \\ &+ \beta_2 TREAT_{k,i} \times POST_{k,t} \\ &+ \beta_3 POST_{k,t} \times CONSTRAINT_{k,i} \\ &+ \alpha_{k,i} + \alpha_{k,j,t} + \varepsilon_{k,i,t} \end{aligned} \tag{5}$$

The only difference relative to equation (4) is the inclusion of the third difference variable, $CONSTRAINT_{k,i}$. $CONSTRAINT_{k,i}$ is one of the measures of firm i's operational or financial constraint. We assign firm i to the high (low) group if firm i's constraint measure is in the upper (lower) tercile one year before the release of the k^{th} edition of IUCN Red List. The coefficient of $TREAT_{k,t} \times CONSTRAINT_{k,i}$ is absorbed by the edition-firm fixed effect ($\alpha_{k,i}$).

We examine two proxies of constraints that capture a firm's adjustment costs or frictions in transitioning away from the affected patent: the number of patents and market leverage. Firms with fewer patents have fewer in-house options to substitute away from the affected patent. Firms with higher leverage will have lower borrowing capacity and face higher borrowing costs in the presence of financial constraints. As such, we hypothesize that treated firms with a smaller patent stock and higher market leverage will be negatively affected by the treatment.

Panel B of Table 7 reports the results. Columns (1)–(2) examine the valuation effects. The triple interaction terms are negative, ranging from -1.122 to -0.949, and are statistically significant at conventional levels. These effects are economically significant: Relative to other treated firms, the valuation (as measured by $Log(Market\text{-}to\text{-}Book)$) of treated firms that have higher adjustment costs is 1.04–1.23 standard deviations lower.

Columns (3)–(4) examine the profitability effects. The triple interaction terms are negative and statistically significant across the measures of constraints, ranging from -0.103 to -0.081. Similar to valuation, these effects are economically large: Relative to other treated firms, the profitability (as measured by $EBIT/Assets$) of treated firms that are constrained is 0.28–0.35 standard deviations lower.

As an additional analysis, Table A10 in the online appendix examines the strength of product market effects and regulatory effects. In columns (1) and (3), we use $LOW\ MARKET\ SHARE$ to identify firms with smaller market share by 6-digit NAICS industry, which are potentially subject to greater product market pressure. We do not find significant effects that lend support to the product market channel. In columns (2) and (4), we use $LOW\ INTERNATIONAL\ ASSETS$ to identify firms with less international operations, which are potentially subject to greater trade regulatory risk. We find a significantly negative effect on valuation, which lends support the trade regulatory channel. The effect on profitability has the wrong sign, but is statistically insignificant.

As robustness checks, Table A11 provides additional proxies of constraints. In columns (1) and (3), we replace $LOW\ PATENT\ STOCK$ with $LOW\ NON\text{-}BIOTECH\ PATENT\ STOCK$. In columns (2) and (4), we replace $HIGH\ LEVERAGE$ with $HIGH\ BOOK\ LEVERAGE$. The results are similar in magnitudes.

Table A12 reports results by restricting the firms in the control group to have at least one species-specific patent, as identified using taxonomic information from GBIF. As a result of this additional sample restriction, the coefficient of $TREAT \times POST$ captures the average treatment effect of the recognition of extinction risk by comparing treated firms with patents that have a species mentioned in a new edition of the IUCN Red List to control firms that have at least one GBIF patent, but are not affected by that particular edition of the Red List. Figure A3 provide the relevant parallel trend plots. The results remain statistically significant and the effects are similar to those in Table 7.

Table A13 addresses concerns over external validity using a sample of private firms in Orbis. As private firms are likely to face tighter operational and financial constraints, we hypothesize that there will be a significantly negative effect on profitability on average in this sample. The coefficient of $TREAT \times POST$ is negative and significant, translating into a 0.14 lower standard deviation in $EBIT/Assets$. Figure A4 graphs the parallel trends.

3.2.4 Extinction risk and adaptation

While the results in Table 7 suggest that treated firms that are constrained have lower cash flows, the cash flows effect (0.28–0.35 standard deviations) alone is unlikely to account for the size of the valuation effects (1.04–1.23 standard deviations). The reduction in valuation likely captures other medium run impacts. For example, treated firms that are constrained may not have the resources to adapt to or transition away from the affected production technology, resulting in the persistent valuation effects documented in Panel B of Table 7.

While the literature on adaptation to biodiversity risk is still in its early stages, considerable attention has been given to studying barriers to adaptation in the climate economics literature (see, for example, Fankhauser, 2017; Mendelsohn, 2000, 2012; Moser and Ekstrom, 2010). Burton (2004) and Smith et al. (2011) examine the role of country level resource and funding constraints in leading to an adaptation deficit. As summarized in Biesbroek et al. (2013), most barriers to adaptation are not specific to climate change. Custódio et al. (2025) provide firm level evidence that operational and financial constraints amplify the impact of rising temperatures on both firm profitability and adaptation. Our preceding results indicate the effects of the recognition of extinction risk is financially material for firms that are operationally or financially more constrained. An important question is whether these constraints also affect how firms adapt to extinction risk.

We employ the difference-in-differences model in Equation (4) to examine the average effects, and the triple difference model in Equation (5) to examine the differential effects based on our measures of constraints. We examine how firms invest in capital expenditures or research and development (R&D) expenses in response to the recognition of extinction risk.

Table 8 reports the results. Panel A reports the average effects. Consistent with the valuation and profitability effects, we do not find any statistically significant average effect. However, after accounting for constraints, we find that constrained firms slash capital investments. Columns (1) and (2) of Panel B show that depending on the proxy,

firms with higher adjustment costs reduce capital investments by 0.64–0.82 standard deviations. Columns (3) and (4) show that firms that are more constrained reduce R&D expenses, but the effects are not significant across specifications. In column (4), we find a statistically significant coefficient of $TREAT \times POST \times HIGH\ LEVERAGE$, but given the coefficient of $TREAT \times POST$ is 0.066, the net negative effects on R&D among constrained firms are quantitatively small.

While firms can adapt to extinction risk via corporate investment or innovation, extinction risk tightens the scope of adaptive strategies these constrained firms can take. Based on the weaker effects in terms of statistical significance and economic magnitudes, our preferred interpretation is that in response to the recognition of extinction risk, treated firms that are constrained prioritize reductions in capital expenditures.

Collectively, the findings in Table 7 and Table 8 indicate that operational and financial constraints are key frictions that make extinction risk financially and economically material. The two-fold impact, first on company valuation and profitability, then on adaptation, indicates that even though extinction risk in the context of corporate patenting may resemble diversifiable risk, constrained firms may still be adversely affected and face obstacles in the transition process.

As robustness checks, Table A14 in the online appendix provides additional proxies of constraints. In columns (1) and (3), we replace $LOW\ PATENT\ STOCK$ with $LOW\ NON\text{-}BIOTECH\ PATENT\ STOCK$. In columns (2) and (4), we replace $HIGH\ LEVERAGE$ with $HIGH\ BOOK\ LEVERAGE$. The results are similar in magnitudes.

Table A15 reports results by restricting the firms in the control group to have at least one species-specific patent, as identified using taxonomic information from GBIF, similar to the exercise in Table A12. Figure A3 provide the relevant parallel trend plots. The results on capital expenditures remain statistically significant, while the effects on R&D becomes insignificant across specifications.

4 Conclusion

In this paper, we examine the value of nature dependence in the context of biotech innovations. Biotech innovations link nature with a firm's production process, which have direct cash flow implications. We designate a patent as a biotech patent if it involves the application of science and technology to living organisms. We find that while the pharmaceutical sector plays an important role, biotech patenting activities span across multiple sectors. Using a sample of granted patents, we find that biotech patents are more valuable, with our most conservative estimate indicating that biotech patents are $191,000 (1982 dollars, approximately $639,000 in 2024 dollars) more valuable than non-biotech patents. This higher incremental value is present regardless of whether a biotech patent is filed by a pharmaceutical company. We provide evidence consistent with that biotech patents provide firms with a competitive advantage in monetizing scientific innovations. We also find that these valuation and cash flow effects are reflected at the company level.

As biotech innovations capitalize on biological resources, we use the recognition of extinction risk in the IUCN Red List to assess the valuation implications of biodiversity loss. We do not find any significant average effects. However, we find that the valuation and profitability of treated firms that are constrained are negatively and significantly affected. We show that treated firms that are constrained reduce capital investments, with weaker effects on R&D. This twofold effect on valuation and adaptation suggests that extinction risk presents significant challenges to constrained firms to transition away from existing technologies.

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Tables

Table 1: Sample Composition

This table reports the industry and CPC code distributions of biotech patents, as defined in Section 2.1.2. Panel A reports industry distribution at the two-digit NAICS code level. Panel B reports CPC code distribution at the CPC section level. The sample consists of biotech patents owned by Compustat firms headquartered in the United States in between 1980 and 2019. We exclude observations without patent values as estimated in Kogan et al. (2017).

Panel A: Industry

		Biotech:	
NAICS Sector	**Sector Description**	**Patent**	**Firm**
11	Agriculture, Forestry, Fishing and Hunting	145	21
21	Mining, Quarrying, and Oil and Gas Extraction	71	18
22	Utilities	30	17
23	Construction	43	11
31	Manufacturing	3172	148
32	Manufacturing	49047	1531
33	Manufacturing	8199	557
42	Wholesale Trade	433	37
44	Retail Trade	8	6
45	Retail Trade	42	6
48	Transportation and Warehousing	15	3
49	Transportation and Warehousing	3	2
51	Information	928	40
52	Finance and Insurance	1732	47
53	Real Estate and Rental and Leasing	94	12
54	Professional, Scientific, and Technical Services	1152	111
56	Administrative and Support and Waste Management and Remediation Services	13	5
61	Educational Services	1	1
62	Health Care and Social Assistance	449	42
71	Arts, Entertainment, and Recreation	2	2
72	Accommodation and Food Services	1	1
99	Unclassified	218	19
Total		65798	2637

Panel B: Cooperative Patent Classification Code

CPC Section	**Description**	**Biotech Patent**
A	Human Necessities	30246
B	Operations and Transport	698
C	Chemistry and Metallurgy	46433
D	Textiles	292
E	Fixed Constructions	20
F	Mechanical Engineering	127
G	Physics	8946
H	Electricity	560
Y	Emerging Cross-sectional Technologies	10101

Table 2: Summary statistics

This table reports summary statistics. Panel A reports summary statistics at the patent level. The sample consists of patents granted to Compustat firms, excluding patents that are granted to the same firm on the same day. Panel B reports summary statistics at the firm-year level. The sample consists of Compustat firms headquartered in the United States that have made at least one patent application. Panel C reports summary statistics at the firm-year level for the stacked difference-in-differences analyses. The sample consists of Compustat firms. Detailed variable definitions are provided in Table A1. Continuous variables are winsorized at the 1% and 99% levels. The sample period begins in 1980 and ends in 2019.

Panel A: Patent level						
Variable	**Mean**	**25th Pct**	**Median**	**75th Pct**	**SD**	**Obs**
Biotech Patent	0.0521	0.0000	0.0000	0.0000	0.2223	153030
Patent Value	20.1740	2.2014	6.1925	17.1485	42.9500	153030
Log(5-Year Importance)	0.2315	0.0806	0.2125	0.3427	0.2301	145533
Commercialization	0.6804	0.0000	1.0000	1.0000	0.4663	153030
Litigated	0.0193	0.0000	0.0000	0.0000	0.1375	153030
Panel B: Firm-year level						
Patent Stock	285.9317	2.0000	11.0000	62.0000	1965.7836	65261
Log(1 + Biotech Patent Stock)	0.2854	0.0000	0.0000	0.0000	0.8718	65261
Log(1 + Non-biotech Patent Stock)	2.7228	0.6931	2.4849	4.0943	2.1768	65261
Log(Market-to-Book)	0.7846	0.2323	0.7148	1.2675	0.8344	65261
EBIT/Assets	0.0557	0.0108	0.0753	0.1413	0.1714	65261
Log(Assets)	5.9077	4.1414	5.6927	7.4936	2.3008	65261
Tobin's Q	2.0594	1.1039	1.4899	2.3184	1.6344	65261
Leverage	0.1417	0.0102	0.0970	0.2244	0.1504	65261
Cash/Assets	0.1965	0.0322	0.1104	0.2954	0.2142	65261
PPE/Assets	0.2285	0.0712	0.1692	0.3265	0.2023	65261
Panel C: Stacked difference-in-differences						
Log(Market-to-Book)	1.6420	1.0651	1.5621	2.1401	0.9107	1182
EBIT/Assets	-0.0295	-0.2155	0.0525	0.1707	0.2940	1182
CapEx/Assets	0.0243	0.0000	0.0000	0.0217	0.0560	1182
R&D/Assets	0.0415	0.0000	0.0000	0.0617	0.0735	1182
Buyback/Assets	0.0330	0.0095	0.0237	0.0430	0.0360	1182
Payout/Assets	0.2086	0.0554	0.1311	0.3146	0.2098	1182
TREAT	0.0355	0.0000	0.0000	0.0000	0.1852	1182
POST	0.5812	0.0000	1.0000	1.0000	0.4936	1182

Table 3: Value of biotech patents

This table reports coefficient estimates from fixed effects Poisson regressions (Equation (1)). The dependent variable is *Patent Value*, the private economic value of patents estimated in Kogan et al. (2017), deflated to 1982 dollars. *Biotech Patent* is an indicator that is equal to one if patent p is a biotech patent, as defined in Section 2.1.2. The sample consists of patents filed by Compustat firms, excluding patents that are granted to the same firm on the same day. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. CPC code is defined at the section level. Industry is defined at the six-digit NAICS code level. Standard errors are double-clustered at the industry and grant year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Patent Value			
	(1)	(2)	(3)	(4)
Biotech Patent	0.056***	0.053*	0.009**	0.010***
	(0.022)	(0.027)	(0.004)	(0.004)
Observations	153,030	153,030	153,030	153,030
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Pseudo R-squared	0.505	0.505	0.893	0.893
Marginal Effect ($M, 1982)	1.165	1.084	0.191	0.200

Table 4: Value of biotech patents: Pharma vs non-pharma

This table reports coefficient estimates from fixed effects Poisson regressions (Equation (1)). The dependent variable is *Patent Value*, the private economic value of patents estimated in Kogan et al. (2017), deflated to 1982 dollars. *Biotech Patent* is an indicator that is equal to one if patent p is a biotech patent, as defined in Section 2.1.2. Continuous variables are winsorized at the 1% and 99% levels. In columns (1) and (2), the sample consists of patents granted to Compustat firms not in the pharmaceutical industry (i.e., excluding firms with SIC code: 2834 or NAICS code: 3254), excluding patents that are granted to the same firm on the same day. In columns (3) and (4), the sample consists of patents granted to Compustat firms in the pharmaceutical industry only (SIC code: 2834 or NAICS code: 3254), excluding patents that are granted to the same firm on the same day. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. CPC code is defined at the section level. Industry is defined at the six-digit NAICS code level. Standard errors are double-clustered at the industry and grant year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Patent Value			
	Non-Pharma Companies		Pharma Companies	
	(1)	(2)	(3)	(4)
Biotech Patent	0.019***	0.021***	0.008***	0.009***
	(0.007)	(0.006)	(0.003)	(0.003)
Observations	132,626	132,626	20,404	20,404
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Pseudo R^2	0.880	0.880	0.921	0.921
Marginal Effect ($M, 1982)	0.348	0.375	0.282	0.306

Table 5: Patent characteristics

This table reports coefficient estimates from fixed effects regressions (Equation (2)). In Panel A, the dependent variable is 5-*year Importance*, patent p's ratio of forward 5-year aggregate patent similarity to backward 5-year aggregate patent similarity in Kelly et al. (2021). In Panel B, the dependent variable is *Commercialization*, an indicator variable that is equal to one if the patent p is clearly intended to be commercialized. In Panel C, the dependent variable is *Litigated*, an indicator variable that is equal to one if patent p was litigated. *Biotech Patent* is an indicator that is equal to one if patent p is a biotech patent, as defined in Section 2.1.2. The sample consists of patents filed by Compustat firms, excluding patents that are granted to the same firm on the same day. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. CPC code is defined at the section level. Industry is defined at the six-digit NAICS code level. Standard errors are double-clustered at the industry and grant year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 5-year Importance				
	(1)	(2)	(3)	(4)
Biotech Patent	0.053***	0.062***	0.031***	0.036***
	(0.019)	(0.018)	(0.010)	(0.010)
Observations	145,533	145,533	145,533	145,533
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R-squared	0.566	0.573	0.668	0.673
Panel B: Commercialization				
	(1)	(2)	(3)	(4)
Biotech Patent	0.008	0.016*	0.032**	0.036**
	(0.009)	(0.009)	(0.014)	(0.014)
Observations	153,030	153,030	153,030	153,030
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R^2	0.0978	0.107	0.169	0.173
Panel C: Litigated				
	(1)	(2)	(3)	(4)
Biotech Patent	-0.015***	-0.014***	-0.005*	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	153,030	153,030	153,030	153,030
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R^2	0.0252	0.0255	0.157	0.157

Table 6: Firm valuation and profitability

This table reports coefficient estimates from fixed effects regressions (Equation (3)). The dependent variable in columns (1) and (2) is $Log(Market\text{-}to\text{-}Book)$, the log of the ratio of firm i's market value of equity to its book value of equity in year t. The dependent variable in columns (3) and (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $Log(1 + Biotech\ Patent\ Stock)$ is the log of one plus firm i's biotech patent stock. $Log(1 + Non\text{-}biotech\ Patent\ Stock)$ is the log of one plus firm i's non-biotech patent stock. $Log(Assets)$ is the log of firm i's total assets in year $t-1$. $Tobin's\ Q$ is firm i's market value of assets in year $t-1$ divided by book value of assets in year $t-1$. $Leverage$ is firm i's book value of debt in year $t-1$ divided by the sum of book value of debt and market value of equity in year $t-1$. $Cash/Assets$ is firm i's cash holdings in year $t-1$ divided by total assets in year $t-1$. $PPE/Assets$ is firm i's net property, plant and equipment in year $t-1$ divided by total assets in year $t-1$. The sample consists of Compustat firms that have made at least one patent application. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. Industry is defined at the six-digit NAICS code level. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
Log(1 + Biotech Patent Stock)	0.101***	0.093***	0.027***	0.016***
	(0.015)	(0.017)	(0.004)	(0.005)
Log(1 + Non-biotech Patent Stock)	-0.000	0.009	-0.005***	-0.004**
	(0.008)	(0.008)	(0.002)	(0.002)
Log(Assets)	-0.126***	-0.144***	-0.001	-0.000
	(0.007)	(0.008)	(0.002)	(0.002)
Tobin's Q	0.178***	0.161***	0.015***	0.014***
	(0.004)	(0.004)	(0.001)	(0.001)
Leverage	-0.121**	0.034	-0.121***	-0.111***
	(0.049)	(0.051)	(0.008)	(0.009)
Cash/Assets	-0.186***	-0.104***	-0.085***	-0.072***
	(0.035)	(0.035)	(0.009)	(0.010)
PPE/Assets	-0.160***	-0.047	-0.084***	-0.105***
	(0.059)	(0.060)	(0.011)	(0.014)
Observations	65,261	65,261	65,261	65,261
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.597	0.637	0.575	0.588

Table 7: Valuation implications of extinction risk

Panel A of this table reports coefficient estimates from difference-in-differences regressions (Equation (4)). Panel B reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in Panel A column (1), Panel B column (1), and Panel B column (3) is $Log(Market\text{-}to\text{-}Book)$, the log of firm i's market value of equity to book value of equity in year t. The dependent variable in Panel A column (2), Panel B column (2), and Panel B column (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ PATENT\ STOCK$ is an indicator variable that is equal to one if firm i is at the lowest patent stock tercile one year before the release of the k^{th} edition of IUCN Red List. $HIGH\ LEVERAGE$ is an indicator variable that is equal to one if firm i is at the highest market leverage tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-differences		
	Log(Market-to-Book)	EBIT/Assets
	(1)	(2)
TREAT×POST	0.019	-0.039
	(0.323)	(0.040)
Observations	1,182	1,182
Edition-Firm	Yes	Yes
Edition-Industry-Year FE	Yes	Yes
Cluster	Firm	Firm
Adjusted R^2	0.627	0.702

Panel B: Triple difference				
	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW PATENT STOCK	-0.949***		-0.103**	
	(0.321)		(0.047)	
TREAT×POST×HIGH LEVERAGE		-1.122***		-0.081*
		(0.322)		(0.045)
TREAT×POST	0.481	0.564*	0.013	0.009
	(0.305)	(0.301)	(0.031)	(0.032)
Observations	1,182	1,182	1,182	1,182
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.628	0.630	0.701	0.702

Table 8: Extinction risk and adaptation

Panel A of this table reports coefficient estimates from difference-in-differences regressions (Equation (4)). Panel B reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in Panel A column (1), Panel B column (1), and Panel B column (3) is $CapEx/Assets$, the ratio of firm i's capital expenditures in year t to assets in year $t-1$. The dependent variable in Panel A column (2), Panel B column (2), and Panel B column (4) is firm i's $R\&D/Assets$, the ratio of R&D expenses in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ PATENT\ STOCK$ is an indicator variable that is equal to one if firm i is at the lowest patent stock tercile one year before the release of the k^{th} edition of IUCN Red List. $HIGH\ LEVERAGE$ is an indicator variable that is equal to one if firm i is at the highest market leverage tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-differences

	CapEx/Assets	R&D/Assets
	(1)	(2)
TREAT×POST	-0.014	0.035
	(0.015)	(0.022)
Observations	1,182	1,182
Edition-Firm	Yes	Yes
Edition-Industry-Year FE	Yes	Yes
Cluster	Firm	Firm
Adjusted R^2	0.508	0.732

Panel B: Triple difference

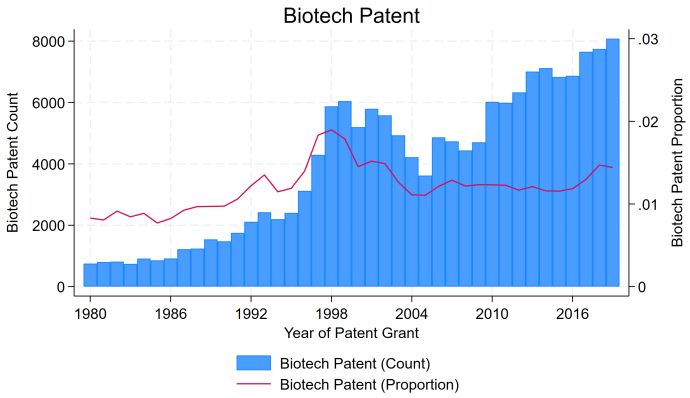
	CapEx/Assets		R&D/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW PATENT STOCK	-0.036***		-0.008	
	(0.011)		(0.030)	
TREAT×POST×HIGH LEVERAGE		-0.046***		-0.065**
		(0.010)		(0.032)
TREAT×POST	0.006	0.010*	0.048*	0.066**
	(0.006)	(0.006)	(0.025)	(0.028)
Observations	1,182	1,182	1,182	1,182
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.513	0.510	0.734	0.732

Figures

Figure 1: Biotech patent: Time trend

This figure plots the time trend of biotech patents. In Panel A, the sample consists of biotech patent grants as defined in Section 2.1.2 in the full patent sample. In Panel B, the sample consists of biotech patent grants in the Compustat sample. The vertical axis on the left corresponds to the bar chart and indicates the count of biotech patent grants. The vertical axis on the right corresponds to the line chart and indicates the proportion of biotech patent grants relative to all patent grants. The sample consists of patents granted in between 1980 and 2019 by the US PTO.

Panel A: Full Patent Sample



Panel B: Compustat Sample

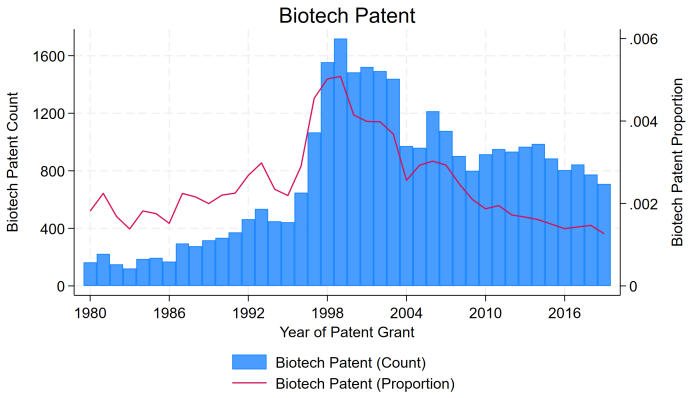


Figure 2: Patent value

This histogram graphs the log of patent values in the patent sample, where patent values are obtained from Kogan et al. (2017). The density of the log of biotech patent values are represented by the bars in light blue. The density of the log of non-biotech patent values are represented by the transparent bars. The sample covers patents granted to publicly traded firms in the United States in between 1980 and 2019.

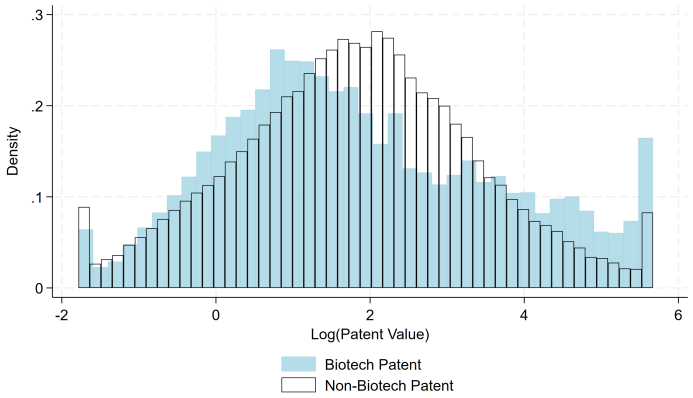
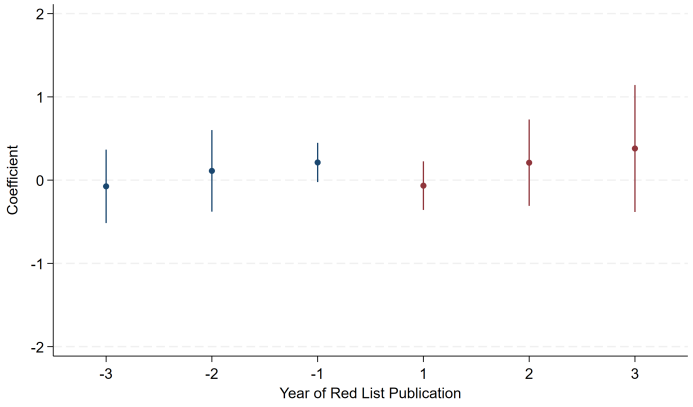


Figure 3: Parallel trends

This set of figures plots the average differences in outcome variables relative to treatment year between firms in the treatment group and the control group in the stacked difference-in-differences sample. The dependent variable is $Log(Market\text{-}to\text{-}Book)$ in Panel A, $EBIT/Assets$ in Panel B, $CapEx/Assets$ in Panel C, and $R\&D/Assets$ in Panel D. The figures report the coefficients from the following regression: $y_{i,t} = \sum_{\tau=-3}^{3} \beta_{t+\tau} TREAT_{k,i} \times RELATIVE\ YEAR_{t-\tau} + \alpha_{k,i} + \alpha_{k,j,t} + \varepsilon_{i,t}$

Panel A: Log(Market-to-Book)



Panel B: EBIT/Assets

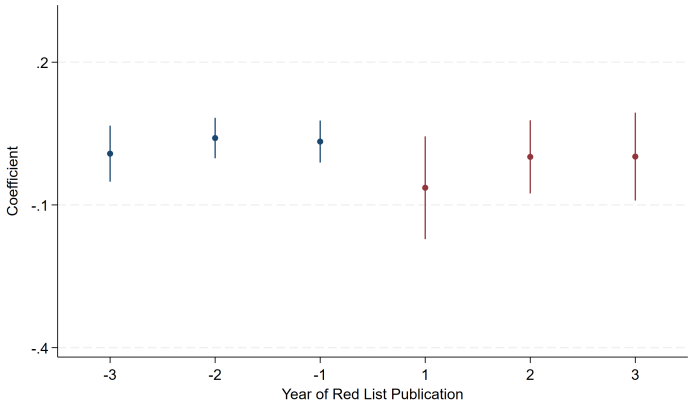
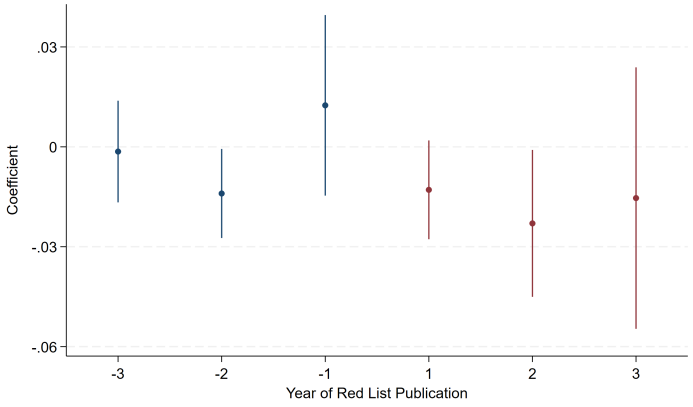
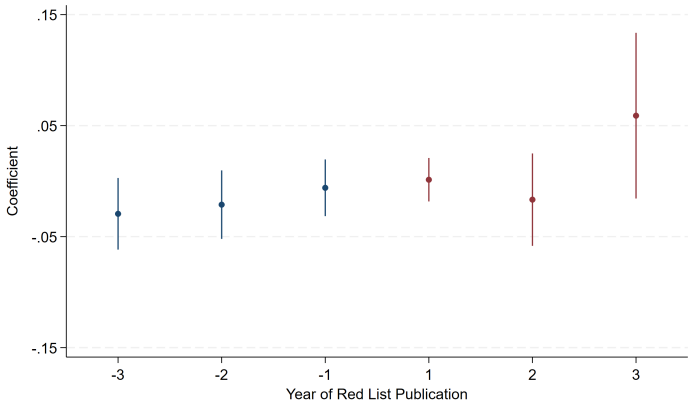


Figure 3: Parallel trends (Continued)

Panel C: CapEx/Assets



Panel D: R&D/Assets



Nature Dependence, Economic Value, and Extinction Risk: Evidence from Biotech Innovations

Internet Appendix

Adrian Lam, David Licher and Moritz Wiedemann

A Appendix

A.1 Tables

Table A1: Variable definitions

This table reports variable definitions. Panel A reports variable definitions at the patent level. The sample consists of patents granted to Compustat firms, excluding patents that are granted to the same firm on the same day. Panel B reports variable definitions at the firm level. The sample consists of Compustat firms headquartered in the United States that have made at least one patent application. Panel C reports variable definitions at the firm level, for the stacked difference-in-differences analyses. The sample consists of Compustat firms. Panel D reports variable definitions at the portfolio level. The sample consists of the time series of returns on portfolios formed by firms that own at least one biotech patent.

Variable	Definition
	Panel A: Patent level
Biotech Patent	Indicator variable that is equal to one if a patent is a biotech patent, as defined in Section 2.1.2.
Patent Value	Private economic value of patents, obtained from Kogan et al. (2017).
5-year Importance	Log of the ratio of forward 5-year aggregate patent similarity to backward 5-year aggregate patent similarity, obtained from Kelly et al. (2021).
Commercialization	Indicator variable that is equal to one if a patent is clearly intended to be comercialized.
Litigated	Indicator variable that is equal to one if a patent has been litigated.
10-year Importance	Log of the ratio of forward 10-year aggregate patent similarity to backward 10-year aggregate patent similarity, obtained from Kelly et al. (2021).
Breakthrough Patent Indicator (5-Year)	Indicator variable that is equal to one if a patent's 5-year importance is in the top decile, obtained from Kelly et al. (2021).
Breakthrough Patent Indicator (10-Year)	Indicator variable that is equal to one if a patent's 10-year importance is in the top decile, obtained from Kelly et al. (2021).
Process Claims	Number of process claims in a patent, obtained from Bena and Simintzi (2023)
Process Innovation Share	Share of process claims in a patent, obtained from Bena and Simintzi (2023)
	Panel B: Firm level
Biotech Patent Stock	The number of the stock of all biotech patent.
Non-biotech Patent Stock	The number of the stock of all non-biotech patent.
Patent Stock	The number of the stock of all patents.
Log(1 + Biotech Patent)	Log of one plus the number of biotech patent stock.
Log(1 + Non-biotech Patent)	Log of one plus the number of non-biotech patent stock.
Log(Market-to-Book)	Log of market-to-book ratio (Compustat: `log((prcc_f× csho)/ceq)`).
EBIT/Assets	Operating income scaled by lagged total assets. (Compustat: `ebit/l.at`)
Log(Assets)	Log of total assets (Compustat: `log(at)`).
Leverage	Book value of debt divided by the sum of book value of debt and market value of equity (Compustat: `(dlc+dltt)/(prcc_f×csho+at-ceq)`).
Cash/Assets	Cash divided by assets (Compustat: `che/at`).
PPE/Assets	Net property, plant and equipment divided by assets (Compustat: `ppent/at`).
Tobin's Q	Market value of assets divided by book value of assets (Compustat: `(at-ceq+prcc_f×csho) / at`).

Table A1: Variable definitions (Continued)

Variable	Definition
Panel C: Firm level (Stacked difference-in-differences sample)	
Buyback/Assets	Amount of share repurchases scaled by lagged total assets (Compustat: `prstkc/L.at`, missing values in `prstkc` are replaced with zero).
Payout/Assets	Amount of share repurchases and dividends scaled by lagged total assets (Compustat: `(prstkc+dv)/L.at`, missing values in `prstkc` and `dv` are replaced with zero).
CapEx/Assets	Capital expenditures scaled by lagged total assets (Compustat: `capx/L.at`, missing values in `capx` are replaced with zero).
R&D/Assets	Research and development expenses scaled by lagged total assets (Compustat: `xrd/L.at`, missing values in `xrd` are replaced with zero).
Debt Issuance	Indicator variable that takes a value of one if a firm has a net increase in book value of debt (Compustat: `dltt + dlc - L.dltt - L.dlc) > 0`.
Equity Issuance	Indicator variable that takes a value of one if a firm has a net increase in book value of equity (Compustat: `ceq - (L.ceq + L.ni - L.dv0) > 0`.
HIGH BOOK LEVERAGE	Indicator variable that is equal to one if a firm is in the lowest book leverage tercile one year before the release of an IUCN Red List edition.
LOW INTERNATIONAL ASSETS	Indicator variable that is equal to one if a firm is in the lowest international assets tercile one year before the release of an IUCN Red List edition, where international assets is the sum of identifiable assets in non-US business segments.
HIGH MARKET LEVERAGE	Indicator variable that is equal to one if a firm is in the lowest market leverage tercile one year before the release of an IUCN Red List edition.
LOW MARKET SHARE	Indicator variable that is equal to one if a firm is in the lowest market share tercile one year before the release of an IUCN Red List edition, where market share is defined is firm sales divided by industry sales at the 6-digit NAICS code level.
LOW NON-BIOTTECH PATENT STOCK	Indicator variable that is equal to one if a firm is in the lowest non-biotech patent stock tercile one year before the release of an IUCN Red List edition.
LOW PATENT STOCK	Indicator variable that is equal to one if a firm is in the lowest patent stock tercile one year before the release of an IUCN Red List edition.
POST	Indicator variable that is equal to one if the period is after the release of an IUCN Red List edition.
TREAT	Indicator variable that is equal to one if a firm has a patent that uses a species identified to be threatened or near threatened in IUCN's Red List.
Panel D: Portfolio level	
CMA	Conservative-minus-aggressive factor, obtained from Ken French's website.
HML	High-minus-low factor, obtained from Ken French's website.
MKT-RF	Equity risk premium, obtained from Ken French's website.
MOM	Momentum factor, obtained from Ken French's website.
RMW	Robust-minus-weak factor, obtained from Ken French's website.
SMB (3-Factor)	Small-minus-big factor, obtained from Ken French's website.
SMB (5-Factor)	Small-minus-big factor, obtained from Ken French's website.
Ret (Equal-weighted)	Equal-weighted return on a portfolio of firms with at least one biotech patent.
Ret (Value-weighted)	Value-weighted return on a portfolio of firms with at least one biotech patent.

Table A2: Industry distribution

This table reports the industry distribution of biotech patents, as defined in Section 2.1.2, at the two-digit NAICS code level. In Panel A, the sample consists of biotech patents owned by Compustat firms in between 1980 and 2019. In Panel B, the sample consists of biotech patents in the patent level regression sample.

Panel A: Patents linked to a Compustat firm

		Biotech identified via:									
		GBIF		PubChem		GBIF/PubChem		OECD		Any	
2-digitNAICS Code	Industry Description	Patent	Firm	Patent	Firm	Patent	Firm	Patent	Firm	Patent	Firm
11	Agriculture, Forestry, Fishing and Hunting	45	13	51	11	94	17	69	17	145	21
21	Mining, Quarrying, and Oil and Gas Extraction	19	8	41	11	52	13	29	13	71	18
22	Utilities	6	4	10	3	15	6	19	14	30	17
23	Construction	12	6	9	3	16	6	36	10	43	11
31	Manufacturing	968	96	1635	114	2332	136	1711	99	3172	148
32	Manufacturing	4938	484	29455	1220	33256	1330	23394	1018	49047	1531
33	Manufacturing	531	135	2033	316	2485	372	6599	418	8199	557
42	Wholesale Trade	88	14	195	20	259	29	281	22	433	37
44	Retail Trade	2	2	0	0	2	2	6	4	8	6
45	Retail Trade	1	1	18	3	19	4	28	4	42	6
48	Transportation and Warehousing	2	1	11	2	13	3	4	1	15	3
49	Transportation and Warehousing	2	1	0	0	2	1	1	1	3	2
51	Information	5	2	435	21	439	21	759	29	928	40
52	Finance and Insurance	156	12	539	35	687	38	1250	41	1732	47
53	Real Estate and Rental and Leasing	7	3	35	7	40	7	78	12	94	12
54	Professional, Scientific, and Technical Services	75	22	493	70	552	80	714	85	1152	111
56	Administrative and Support and Waste Management and Remediation Services	1	1	4	3	5	3	10	5	13	5
61	Educational Services	0	0	0	0	0	0	1	1	1	1
62	Health Care and Social Assistance	5	2	127	24	131	24	351	37	449	42
71	Arts, Entertainment, and Recreation	0	0	1	1	1	1	1	1	2	2
72	Accommodation and Food Services	0	0	1	1	1	1	1	1	1	1
99	Unclassified	26	9	46	15	71	18	174	17	218	19

Panel B: Patent level regression sample

		Biotech identified via:									
		GBIF		PubChem		GBIF/PubChem		OECD		Any	
2-digit NAICS Code	Industry Description	Patent	Firm	Patent	Firm	Patent	Firm	Patent	Firm	Patent	Firm
11	Agriculture, Forestry, Fishing and Hunting	4	2	10	3	12	3	7	3	17	4
21	Mining, Quarrying, and Oil and Gas Extraction	2	1	0	0	2	1	1	1	3	2
31	Manufacturing	25	4	53	11	68	13	68	7	107	14
32	Manufacturing	431	90	4177	317	4517	337	3273	281	6787	403
33	Manufacturing	19	11	138	48	154	54	525	67	636	90
42	Wholesale Trade	0	0	17	2	17	2	19	2	28	3
51	Information	0	0	45	1	45	1	90	4	97	4
52	Finance and Insurance	0	0	0	0	0	0	1	1	1	1
53	Real Estate and Rental and Leasing	0	0	10	2	10	2	24	3	27	3
54	Professional, Scientific, and Technical Services	26	8	90	15	106	15	133	18	206	22
56	Administrative and Support and Waste Management and Remediation Services	1	1	1	1	2	1	1	1	3	2
62	Health Care and Social Assistance	1	1	9	3	10	3	55	9	63	9
Total		509	118	4550	403	4943	432	4197	397	7975	557

Table A3: Additional Summary statistics

This table reports summary statistics. Panel A reports summary statistics at the patent level. The sample consists of patents granted to Compustat firms, excluding patents that are granted to the same firm on the same day. Panel B reports summary statistics at the firm-year level. The sample consists of Compustat firms headquartered in the United States that have made at least one patent application. Panel C reports summary statistics at the portfolio level. The sample consists of the time series of returns on a biotech portfolio. Panel D reports summary statistics at the firm-year level for the stacked difference-in-differences analyses. The sample consists of Compustat firms. Panel E reports summary statistics at the firm-year level for the stacked difference-in-differences analyses. The sample consists of private firms in Orbis. Detailed variable definitions are provided in Table A1. Continuous variables are winsorized at the 1% and 99% levels. The sample period begins in 1980 and ends in 2019.

Panel A: Patent level						
Variable	**Mean**	**25th Pct**	**Median**	**75th Pct**	**SD**	**Obs**
Breakthrough Patent [5-Year]	0.1374	0.0000	0.0000	0.0000	0.3443	145540
Breakthrough Patent [10-Year]	0.1530	0.0000	0.0000	0.0000	0.3600	118264
Log(10-Year Importance)	0.9715	0.7807	0.9277	1.1108	0.2737	118263
Panel B: Firm-year level						
Log(Tobin's Q)	0.4990	0.0909	0.3798	0.8027	0.5519	145540
Net Income/Assets	0.0084	-0.0182	0.0391	0.0904	0.1722	118264
Panel C: Portfolio level						
CMA	0.2641	-0.9900	0.0850	1.4450	1.9706	480
HML	0.2323	-1.4400	0.1100	1.7200	2.9306	480
MKT-RF	0.6791	-1.9300	1.1300	3.4700	4.3990	480
MOM	0.5645	-1.1350	0.6300	2.8900	4.4711	480
RWA	0.3552	-0.7450	0.3350	1.3250	2.3688	480
SMB (3 Factor)	0.0769	-1.7200	0.0750	1.7150	2.9806	480
SMB (5 Factor)	0.0947	-1.5800	0.0350	1.8550	2.8677	480
Ret (Equal-weighted)	0.7219	-2.2767	0.8724	3.9196	5.2339	480
Ret (Value-weighted)	0.7466	-2.2924	1.0985	4.3292	5.7324	480
Panel D: Stacked difference-in-differences (Compustat)						
Log(Tobin's Q)	1.1296	0.7250	1.1452	1.5573	0.5949	516
Net Income/Assets	0.0465	-0.0124	0.0770	0.1404	0.1822	516
ΔNet PPE/Assets	0.0154	-0.0024	0.0059	0.0225	0.0388	516
Panel E: Stacked difference-in-differences (Orbis)						
EBIT/Assets	-0.0001	-0.0207	0.0440	0.1029	0.2082	3356
TREAT	0.0447	0.0000	0.0000	0.0000	0.2067	3356
POST	0.5900	0.0000	1.0000	1.0000	0.4919	3356

Table A4: Patent characteristics: Alternative measures of scientific value

This table reports coefficient estimates from fixed effects regressions (Equation (2)). In Panel A, the dependent variable is *Breakthrough Patent Indicator* (5-*year*), an indicator variable that is equal to one if the 5-year importance of patent p falls into the top decile (Kelly et al., 2021). In Panel B, the dependent variable is 10-*Year Importance*, the ratio of forward 10-year aggregate patent similarity to backward 10-year aggregate patent similarity in Kelly et al. (2021). In Panel C, the dependent variable is *Breakthrough Patent Indicator* (10-*year*), an indicator variable that is equal to one if the 10-year importance of patent p falls into the top decile (Kelly et al., 2021). *Biotech Patent* is an indicator that is equal to one if patent p is a biotech patent, as defined in Section 2.1.2. The sample consists of patents filed by Compustat firms, excluding patents that are granted to the same firm on the same day. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. In Panel A, the sample period begins in 1980 and ends in 2016 to take into account of truncation bias. In Panel B, the sample period begins in 1980 and ends in 2016. In Panel C, the sample period begins in 1980 and ends in 2011 to take into account of truncation bias. CPC code is defined at the section level. Industry is defined at the six-digit NAICS code level. Standard errors are double-clustered at the industry and grant year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Breakthrough Patent Indicator (5-year)				
	(1)	(2)	(3)	(4)
Biotech Patent	0.084***	0.090***	0.049***	0.051***
	(0.028)	(0.028)	(0.015)	(0.014)
Observations	145,539	145,539	145,534	145,534
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R-squared	0.240	0.244	0.366	0.369
Panel B: 10-year Importance				
	(1)	(2)	(3)	(4)
Biotech Patent	0.060**	0.072***	0.035**	0.041***
	(0.025)	(0.023)	(0.014)	(0.014)
Observations	118,262	118,262	118,257	118,257
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R-squared	0.531	0.542	0.639	0.646
Panel C: Breakthrough Patent Indicator (10-year)				
	(1)	(2)	(3)	(4)
Biotech Patent	0.090***	0.096***	0.052***	0.055***
	(0.030)	(0.028)	(0.017)	(0.016)
Observations	118,263	118,263	118,258	118,258
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R-squared	0.250	0.257	0.374	0.378

Table A5: Patent characteristics: Processes

Panel A of this table reports coefficient estimates from fixed effects Poisson regressions (Equation 1). The dependent variable is *Process Claims*, the number of process claims in a patent (Bena and Simintzi, 2023). Panel B reports coefficient estimates from fixed effects regressions (Equation 2). The dependent variable is *Process InnovationShare*, the share of process claims in a patent (Bena and Simintzi, 2023). *Biotech Patent* is an indicator that is equal to one if patent p is a biotech patent, as defined in Section 2.1.2. The sample consists of patents filed by Compustat firms, excluding patents that are granted to the same firm on the same day. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. CPC code is defined at the section level. Industry is defined at the six-digit NAICS code level. Standard errors are double-clustered at the industry and grant year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Process claims				
	(1)	(2)	(3)	(4)
Biotech Patent	0.028	-0.019	0.052	0.024
	(0.060)	(0.044)	(0.045)	(0.036)
Observations	149,743	149,743	145,101	145,101
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Pseudo R-squared	0.155	0.161	0.268	0.271
Marginal Effect	0.191	-0.129	0.369	0.169
Panel B: Process innovation share				
	(1)	(2)	(3)	(4)
Biotech Patent	0.029	0.013	0.034*	0.026
	(0.023)	(0.017)	(0.020)	(0.016)
Observations	152,986	152,986	152,983	152,983
CPC FE	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	No	No
Firm-Year FE	No	No	Yes	Yes
Cluster	Industry & Year	Industry & Year	Industry & Year	Industry & Year
Adjusted R-squared	0.125	0.133	0.202	0.207

Table A6: Firm valuation and profitability (Excluding pharmaceutical firms)

This table reports coefficient estimates from fixed effects regressions (Equation (3)). The dependent variable in columns (1) and (2) is $Log(Market\text{-}to\text{-}Book)$, the log of the ratio of firm i's market value of equity to its book value of equity in year t. The dependent variable in columns (3) and (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $Log(1 + Biotech\ Patent\ Stock)$ is the log of one plus firm i's biotech patent stock. $Log(1 + Non\text{-}biotech\ Patent\ Stock)$ is the log of one plus firm i's non-biotech patent stock. $Log(Assets)$ is the log of firm i's total assets in year $t-1$. $Tobin's\ Q$ is firm i's market value of assets in year $t-1$ divided by book value of assets in year $t-1$. $Leverage$ is firm i's book value of debt in year $t-1$ divided by the sum of book value of debt and market value of equity in year $t-1$. $Cash/Assets$ is firm i's cash holdings in year $t-1$ divided by total assets in year $t-1$. $PPE/Assets$ is firm i's net property, plant and equipment in year $t-1$ divided by total assets in year $t-1$. The sample consists of Compustat firms that have made at least one patent application, and excludes firms in the pharmaceutical industry (SIC code: 2834 or NAICS code: 3254). Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. Industry is defined at the six-digit NAICS code level. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Excluding Pharmaceutical Companies			
	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
Log(1 + Biotech Patent Stock)	0.104***	0.094***	0.012***	0.009**
	(0.021)	(0.021)	(0.003)	(0.004)
Log(1 + Non-biotech Patent Stock)	-0.001	0.007	-0.005***	-0.004**
	(0.008)	(0.009)	(0.002)	(0.002)
Log(Assets)	-0.126***	-0.147***	-0.005***	-0.005***
	(0.008)	(0.009)	(0.002)	(0.002)
Tobin's Q	0.185***	0.165***	0.017***	0.017***
	(0.004)	(0.004)	(0.001)	(0.001)
Mkt Lev	-0.150***	0.001	-0.109***	-0.098***
	(0.050)	(0.052)	(0.007)	(0.008)
Cash/Assets	-0.211***	-0.117***	-0.068***	-0.052***
	(0.037)	(0.037)	(0.009)	(0.010)
PPE/Assets	-0.193***	-0.081	-0.082***	-0.108***
	(0.061)	(0.062)	(0.011)	(0.013)
Observations	60,541	60,530	60,541	60,530
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.588	0.634	0.542	0.569

Table A7: Firm valuation and profitability: Additional specifications

This table reports coefficient estimates from fixed effects regressions (Equation (3)). The dependent variable in columns (1) and (2) is $Log(Market\text{-}to\text{-}Book)$, the log of the ratio of firm i's market value of equity to its book value of equity in year t. The dependent variable in columns (3)–(6) is $Log(Tobin's\ Q)$, the log of firm i's market value of assets in year t divided by book value of assets in year t. The dependent variable in columns (7) and (8) is firm i's $Net\ Income/Assets$, the ratio of EBIT in year t to assets in year $t-1$. $Log(1 + Biotech\ Patent\ Stock)$ is the log of one plus firm i's biotech patent stock. $Log(1 + Non\text{-}biotech\ Patent\ Stock)$ is the log of one plus firm i's non-biotech patent stock. $Log(Assets)$ is the log of firm i's total assets in year $t-1$. $Log(Assets)$ is the log of firm i's total assets in year $t-1$. $Tobin's\ Q$ is firm i's market value of assets in year $t-1$ divided by book value of assets in year $t-1$. $Leverage$ is firm i's book value of debt in year $t-1$ divided by the sum of book value of debt and market value of equity in year $t-1$. $Cash/Assets$ is firm i's cash holdings in year $t-1$ divided by total assets in year $t-1$. $PPE/Assets$ is firm i's net property, plant and equipment in year $t-1$ divided by total assets in year $t-1$. The sample consists of Compustat firms that have made at least one patent application. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. Industry is defined at the six-digit NAICS code level. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(Market-to-Book)		Log(Tobin's Q)				Net Income/Assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(1 + Biotech Patent Stock)	0.101***	0.096***	0.084***	0.066***	0.045***	0.038***	0.021***	0.014***
	(0.015)	(0.017)	(0.012)	(0.015)	(0.008)	(0.010)	(0.004)	(0.005)
Log(1 + Non-biotech Patent Stock)			-0.037***	-0.021***	-0.013***	-0.007	-0.001	-0.000
			(0.006)	(0.007)	(0.004)	(0.005)	(0.001)	(0.002)
Log(Assets)	-0.126***	-0.142***	-0.087***	-0.104***	-0.066***	-0.077***	-0.005***	-0.005**
	(0.007)	(0.008)	(0.005)	(0.006)	(0.004)	(0.005)	(0.002)	(0.002)
Tobin's Q	0.178***	0.160***			0.140***	0.129***	0.012***	0.012***
	(0.004)	(0.004)			(0.002)	(0.003)	(0.001)	(0.001)
Leverage	-0.121**	0.033	-0.724***	-0.619***	-0.366***	-0.306***	-0.126***	-0.120***
	(0.049)	(0.051)	(0.028)	(0.030)	(0.021)	(0.023)	(0.008)	(0.009)
Cash/Assets	-0.185***	-0.106***	0.207***	0.209***	0.029	0.062***	-0.035***	-0.022**
	(0.034)	(0.035)	(0.028)	(0.027)	(0.021)	(0.021)	(0.009)	(0.010)
PPE/Assets	-0.160***	-0.046	-0.022	0.014	-0.030	-0.009	-0.058***	-0.071***
	(0.059)	(0.060)	(0.039)	(0.041)	(0.028)	(0.030)	(0.011)	(0.014)
Observations	65,261	65,261	65,261	65,261	65,261	65,261	65,257	65,257
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.597	0.637	0.608	0.639	0.687	0.704	0.486	0.480

Table A8: Firm valuation and profitability: Alternative independent variables

This table reports coefficient estimates from fixed effects regressions (Equation (3)). The dependent variable in columns (1) and (2) is $Log(Market\text{-}to\text{-}Book)$, the log of the ratio of firm i's market value of equity to its book value of equity in year t. The dependent variable in columns (3) and (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. *Biotech Patent %* is the ratio of firm i's number of biotech patent stock divided by the number of all patents. $Log(Patent\ Stock)$ is the log of firm i's patent stock. $Log(Assets)$ is the log of firm i's total assets in year $t-1$. $Tobin's\ Q$ is firm i's market value of assets in year $t-1$ divided by book value of assets in year $t-1$. $Leverage$ is firm i's book value of debt in year $t-1$ divided by the sum of book value of debt and market value of equity in year $t-1$. $Cash/Assets$ is firm i's cash holdings in year $t-1$ divided by total assets in year $t-1$. $PPE/Assets$ is firm i's net property, plant and equipment in year $t-1$ divided by total assets in year $t-1$. The sample consists of Compustat firms that have made at least one patent application, and excludes firms in the pharmaceutical industry (SIC code: 2834 or NAICS code: 3254). Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. The sample period begins in 1980 and ends in 2019. Industry is defined at the six-digit NAICS code level. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
Biotech Patent%×Log(Patent Stock)	0.132***	0.100**	0.083***	0.036**
	(0.034)	(0.051)	(0.012)	(0.017)
Biotech Patent%	-0.240	-0.143	-0.251***	-0.138**
	(0.170)	(0.201)	(0.063)	(0.065)
Log(Patent Stock)	0.008	0.018**	-0.006***	-0.005**
	(0.008)	(0.009)	(0.002)	(0.002)
Log(Assets)	-0.133***	-0.151***	0.000	0.002
	(0.009)	(0.010)	(0.002)	(0.002)
Tobin's Q	0.178***	0.156***	0.014***	0.014***
	(0.004)	(0.004)	(0.001)	(0.001)
Mkt Lev	-0.054	0.114**	-0.120***	-0.115***
	(0.054)	(0.058)	(0.008)	(0.010)
Cash/Assets	-0.142***	-0.076**	-0.079***	-0.070***
	(0.037)	(0.038)	(0.010)	(0.011)
PPE/Assets	-0.188***	-0.060	-0.084***	-0.095***
	(0.065)	(0.071)	(0.013)	(0.016)
Observations	54,093	52,599	54,093	52,599
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Cluster	Firm	Firm	Firm	Firm
Adjusted R2	0.616	0.655	0.598	0.605

Table A9: Portfolio returns

This table reports coefficient estimates from factor models. In columns (1)–(4), the dependent variable is the return in excess of the risk-free rate on a value-weighted portfolios of biotech patent-filing firms. In column (5)–(8), the dependent variable is the return in excess of the risk-free rate on a equally weighted portfolios of biotech patent-filing firms. The sample consists of monthly returns of portfolios formed by Compustat firms that have a biotech patent. α is the risk-adjusted excess return. Standard errors are calculated using Newey and West (1987). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Excess Returns							
	Value-Weight				Equal-weight			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mkt-RF	0.919***	0.922***	0.885***	0.943***	0.912***	0.881***	0.850***	0.882***
	(0.067)	(0.069)	(0.069)	(0.075)	(0.057)	(0.058)	(0.047)	(0.053)
SMB		-0.001	0.004	-0.034		0.282***	0.286***	0.177***
		(0.096)	(0.100)	(0.101)		(0.064)	(0.072)	(0.064)
HML		0.021	-0.049	-0.081		0.078	0.017	-0.042
		(0.087)	(0.080)	(0.124)		(0.055)	(0.053)	(0.080)
MOM			-0.167***				-0.143***	
			(0.064)				(0.039)	
RMW				-0.078				-0.264***
				(0.123)				(0.075)
CMA				0.264*				0.255**
				(0.158)				(0.115)
α	0.123	0.115	0.251	0.086	0.103	0.084	0.199	0.142
	(0.221)	(0.208)	(0.232)	(0.237)	(0.172)	(0.155)	(0.161)	(0.162)
Observations	480	480	480	480	480	480	480	480
Newey-West Lags	12	12	12	12	12	12	12	12

Table A10: Valuation implications of extinction risk: Suggestive evidence on channels

This table reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in columns (1) and (2) is $Log(Market\text{-}to\text{-}Book)$, the log of firm i's market value of equity in year t divided by book value of equity in year t. The dependent variable in columns (3) and (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ MARKET\ SHARE$ is an indicator variable that is equal to one if firm i is at the lowest market share tercile one year before the release of the k^{th} edition of IUCN Red List. $LOW\ INTERNATIONAL\ ASSETS$ is an indicator variable that is equal to one if firm i is at the lowest international assets tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW MARKET SHARE	0.082		0.009	
	(0.548)		(0.062)	
TREAT×POST×LOW INTERNATIONAL ASSETS		-1.009**		0.064
		(0.399)		(0.101)
TREAT×POST	-0.004	0.609*	-0.042	-0.103*
	(0.472)	(0.344)	(0.056)	(0.059)
Observations	1,182	1,182	1,182	1,182
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adj R-squared	0.626	0.629	0.701	0.702

Table A11: Valuation implications of extinction risk: Additional proxies for constraints

This table reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in columns (1) and (2) is $Log(Market\text{-}to\text{-}Book)$, the log of firm i's market value of equity in year t divided by book value of equity in year t. The dependent variable in columns (3) and (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ NON\text{-}BIOTECH\ PATENT\ STOCK$ is an indicator variable that is equal to one if firm i is at the lowest non-biotech patent stock tercile one year before the release of the k^{th} edition of IUCN Red List. $HIGH\ BOOK\ LEVERAGE$ is an indicator variable that is equal to one if firm i is at the highest book leverage tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW NON-BIOTECH PATENT STOCK	-1.081***		-0.102**	
	(0.336)		(0.045)	
TREAT×POST×HIGH BOOK LEVERAGE		-1.122***		-0.081*
		(0.322)		(0.045)
TREAT×POST	0.517	0.564*	0.012	0.009
	(0.315)	(0.301)	(0.030)	(0.032)
Observations	1,182	1,182	1,182	1,182
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adj R-squared	0.629	0.630	0.701	0.702

Table A12: Valuation implications of extinction risk: Alternative control group

Panel A of this table reports coefficient estimates from difference-in-differences regressions (Equation (4)). Panel B reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in Panel A column (1), Panel B column (1), and Panel B column (2) is $Log(Market\text{-}to\text{-}Book)$, the log of firm i's market value of equity in year t divided by book value of equity in year t. The dependent variable in Panel A column (2), Panel B columns (3), and Panel B column (4) is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ PATENT\ STOCK$ is an indicator variable that is equal to one if firm i is at the lowest patent stock tercile one year before the release of the k^{th} edition of IUCN Red List. $HIGH\ LEVERAGE$ is an indicator variable that is equal to one if firm i is at the highest market leverage tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample, with firms in the control group restricted to firms with a patent application that mentions a species in the pre-period. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-differences

	Log(Market-to-Book)	EBIT/Assets
	(1)	(2)
TREAT×POST	-0.032	-0.046
	(0.326)	(0.043)
Observations	516	516
Edition-Firm	Yes	Yes
Edition-Industry-Year FE	Yes	Yes
Cluster	Firm	Firm
Adjusted R^2	0.679	0.720

Panel B: Triple difference

	Log(Market-to-Book)		EBIT/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW PATENT STOCK	-0.691*		-0.147***	
	(0.349)		(0.037)	
TREAT×POST×HIGH LEVERAGE		-1.297***		-0.081***
		(0.358)		(0.030)
TREAT×POST	0.290	0.671**	0.021	0.018
	(0.289)	(0.328)	(0.018)	(0.014)
Observations	516	516	516	516
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adj R-squared	0.690	0.689	0.722	0.725

Table A13: Cash flow effects of extinction risk: Private firm sample

This table reports coefficient estimates from difference-in-differences regressions (Equation (4)). The dependent variable is firm i's $EBIT/Assets$, the ratio of operating profit in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of private firms in Orbis in a stacked difference-in-differences sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	EBIT/Assets	
	(1)	(2)
TREAT×POST	-0.030**	-0.030**
	(0.014)	(0.014)
Observations	3,356	3,356
Edition-Firm	Yes	Yes
Edition-Country-Year	Yes	No
Edition-Industry-Year FE	Yes	No
Edition-Country-Industry-Year FE	No	Yes
Cluster	Firm	Firm
Adjusted R^2	0.749	0.749

Table A14: Extinction risk and adaptation: Alternative proxies for constraints

This table reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in columns (1) and (2) is $CapEx/Assets$, the ratio of firm i's capital expenditures in year t to assets in year $t-1$. The dependent variable in columns (3) and (4) is firm i's $R\&D/Assets$, the ratio of R&D expenses in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ NON\text{-}BIOTECH\ PATENT\ STOCK$ is an indicator variable that is equal to one if firm i is at the lowest non-biotech patent stock tercile one year before the release of the k^{th} edition of IUCN Red List. $HIGH\ BOOK\ LEVERAGE$ is an indicator variable that is equal to one if firm i is at the highest book leverage tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	CapEx/Assets		R&D/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW NON-BIOTECH PATENT STOCK	-0.038***		-0.035	
	(0.011)		(0.031)	
TREAT×POST×HIGH BOOK LEVERAGE		-0.046***		-0.065**
		(0.010)		(0.032)
TREAT×POST	0.006	0.010*	0.054**	0.066**
	(0.006)	(0.006)	(0.026)	(0.028)
Observations	1,182	1,182	1,182	1,182
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adj R-squared	0.512	0.510	0.732	0.732

Table A15: Extinction risk and adaptation: Alternative control group

Panel A of this table reports coefficient estimates from difference-in-differences regressions (Equation (4)). Panel B reports coefficient estimates from from triple difference regressions (Equation (5)). The dependent variable in Panel A column (1), Panel B column (1), and Panel B column (3) is $CapEx/Assets$, the ratio of firm i's capital expenditures in year t to assets in year $t-1$. The dependent variable in Panel A column (2), Panel B column (2), and Panel B column (4) is firm i's $R\&D/Assets$, the ratio of R&D expenses in year t to assets in year $t-1$. $TREAT$ is an indicator variable that is equal to one if firm i has a patent that uses a species identified to be threatened or near threatened in the k^{th} edition of IUCN Red List. $POST$ is an indicator variable that is equal to one if year t is greater than the year of release of the k^{th} edition of IUCN Red List. $LOW\ PATENT\ STOCK$ is an indicator variable that is equal to one if firm i is at the lowest patent stock tercile one year before the release of the k^{th} edition of IUCN Red List. $HIGH\ LEVERAGE$ is an indicator variable that is equal to one if firm i is at the highest market leverage tercile one year before the release of the k^{th} edition of IUCN Red List. Other coefficients are suppressed for brevity. Continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Table A1. Industry is defined at the six-digit NAICS code level. The sample consists of Compustat firms in the stacked difference-in-differences sample, with firms in the control group restricted to firms with a patent application that mentions a species in the pre-period. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-differences

	CapEx/Assets	R&D/Assets
	(1)	(2)
TREAT×POST	-0.012	0.018
	(0.012)	(0.016)
Observations	516	516
Edition-Firm	Yes	Yes
Edition-Industry-Year FE	Yes	Yes
Cluster	Firm	Firm
Adjusted R^2	0.489	0.825

Panel B: Triple difference

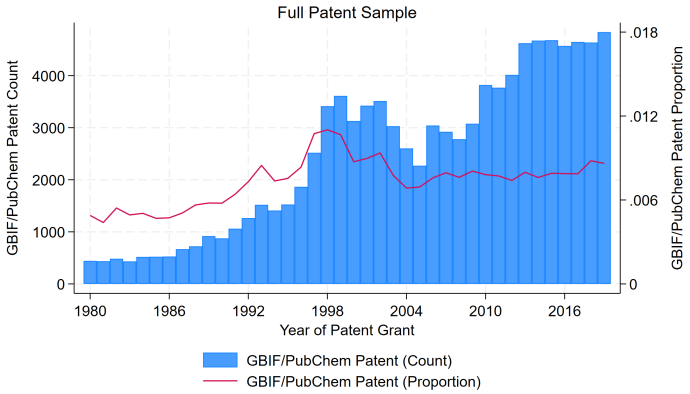
	CapEx/Assets		R&D/Assets	
	(1)	(2)	(3)	(4)
TREAT×POST×LOW PATENT STOCK	-0.045***		0.006	
	(0.010)		(0.034)	
TREAT×POST×HIGH LEVERAGE		-0.041***		-0.042
		(0.009)		(0.026)
TREAT×POST	0.008	0.010	0.017	0.042
	(0.007)	(0.007)	(0.027)	(0.025)
Observations	516	516	516	516
Edition-Firm	Yes	Yes	Yes	Yes
Edition-Industry-Year FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
Adj R-squared	0.498	0.496	0.827	0.824

A.2 Figures

Figure A1: Biotech patent (alternative definitions): Time trend (Full patent sample)

This figure plots the time trend of biotech patents using alternative definitions. In Panel A, biotech patents are defined as patents with abstracts explicitly mentioning gene, protein, cell, or species names. In Panel B, biotech patents are defined as patents with CPC codes that fall under OECD's biotechnology patent categories (Friedrichs and van Beuzekom, 2018). The vertical axis on the left corresponds to the bar chart and indicates the count of biotech patent grants. The vertical axis on the right corresponds to the line chart and indicates the proportion of biotech patent grants relative to all patent grants. The sample consists of patents granted in between 1980 and 2019 by the US PTO.

Panel A: GBIF/PubChem Patent



Panel B: OECD Patent

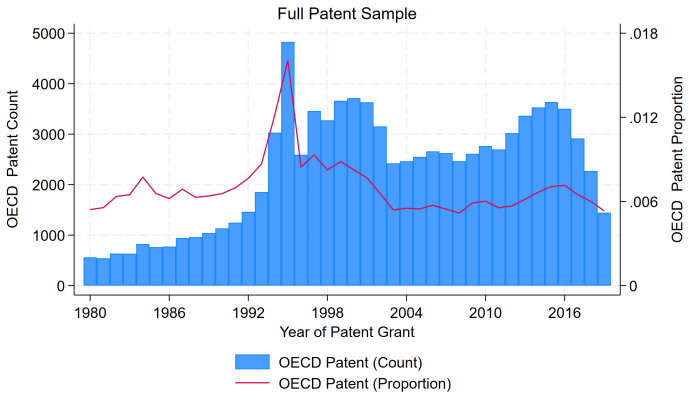
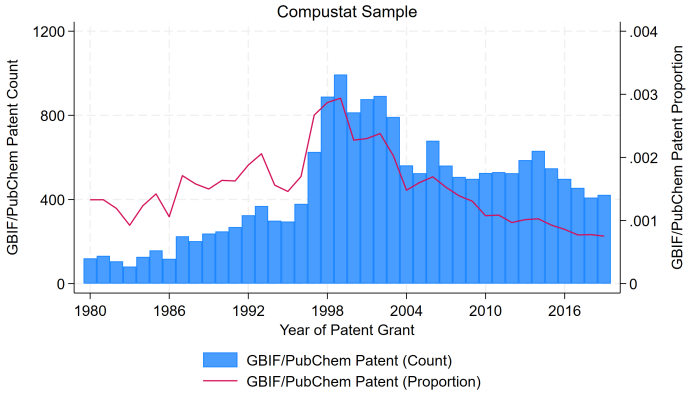


Figure A2: Biotech patent (alternative definitions): Time trend (Compustat sample)

This figure plots the time trend of biotech patents using alternative definitions. In Panel A, biotech patents are defined as patents with abstracts explicitly mentioning gene, protein, cell, or species names. In Panel B, biotech patents are defined as patents with CPC codes that fall under OECD's biotechnology patent categories (Friedrichs and van Beuzekom, 2018). The vertical axis on the left corresponds to the bar chart and indicates the count of biotech patent applications. The vertical axis on the right corresponds to the line chart and indicates the proportion of biotech patent applications relative to all patent applications. The sample consists of patent granted by the US PTO to Compustat firms in between 1980 and 2019.

Panel A: GBIF/PubChem Patent



Panel B: OECD Patent

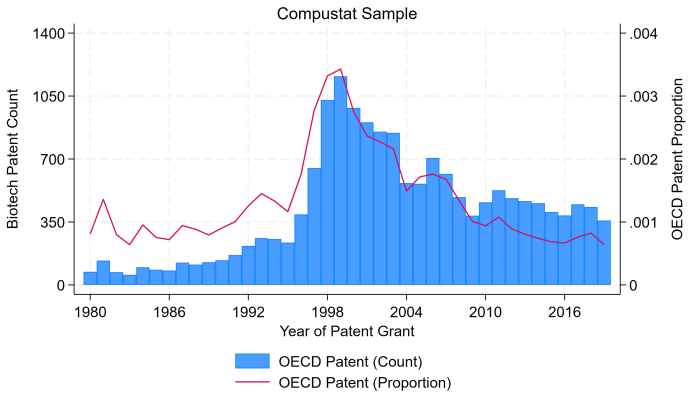
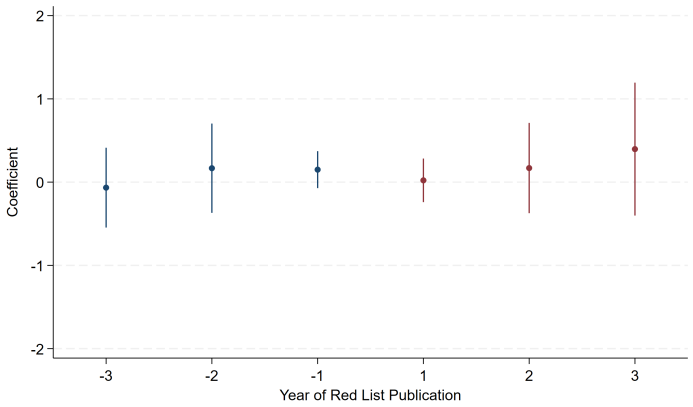


Figure A3: Parallel trends: Alternative dependent variables

This set of figures plots the average differences in outcome variables relative to treatment year between firms in the treatment group and the control group in the stacked difference-in-differences sample. In Panel A, the dependent variable is $Log(Tobin's\ Q)$. In Panel B, the dependent variable is $Net\ Income/Assets$. Detailed variable definitions are provided in Table A1. The figures report the coefficients from the following regression: $y_{i,t} = \sum_{\tau=-3}^{3} \beta_{t+\tau} TREAT_{k,i} \times RELATIVE\ YEAR_{t-\tau} + \alpha_{k,i} + \alpha_{k,j,t} + \varepsilon_{i,t}$

Panel A: Log(Tobin's Q)



Panel B: Net Income/Assets

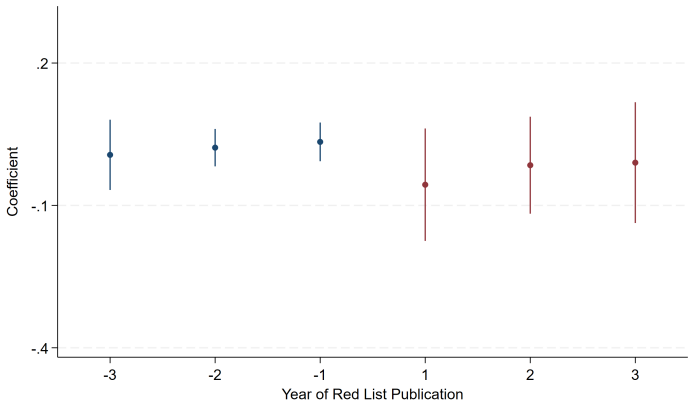
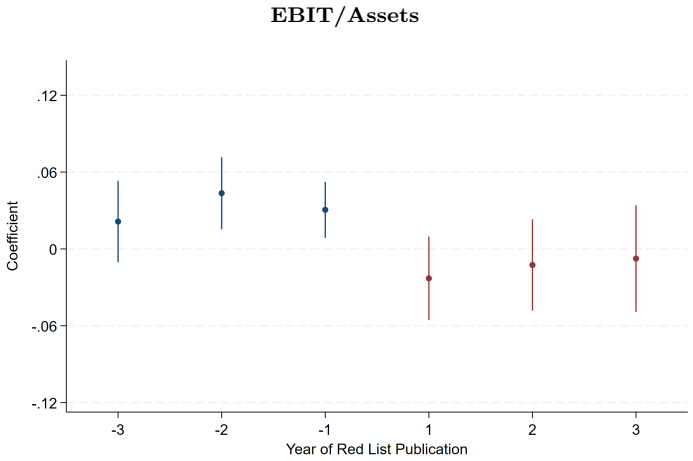


Figure A4: Parallel trends: Alternative sample

This set of figures plots the average differences in outcome variables relative to treatment year between firms in the treatment group and the control group in the stacked difference-in-differences sample. This sample consists of private firms in Orbis. The dependent variable is $EBIT/Assets$. Detailed variable definitions are provided in Table A1. The figures report the coefficients from the following regression: $y_{i,t} = \sum_{\tau=-3}^{3} \beta_{t+\tau} TREAT_{k,i} \times RELATIVE\ YEAR_{t-\tau} + \alpha_{k,i} + \alpha_{k,j,t} + \varepsilon_{i,t}$



B Patent examples

Table B1: Biotech patent examples

This table provides biotech patent examples. Panel A shows two patents with abstracts mentioning species names. Panel B shows two patents with abstracts mentioning a gene, protein or cell. Panel C shows two patents with CPC codes falling under OCED's biotech patent classification.

Panel A: GBIF patents

Patent Number	Abstract	Publication Date	Application Date	CPC Codes
US8075930B2	A method of making a low molecular weight fraction of Phyllanthus niruri is provided. Such low molecular weight fraction is particularly useful for treating the skin, for example skin in need of treatment for signs of aging, for reducing inflammation, or for skin lightening.	2011-12-13	2010-10-01	A61K 36/28; A61K 36/47; A61P 29/00
USPP20885P3	A new pineapple (Ananas comosus) variety of the Bromeliaceae family was developed from a cross made by Dole between the commercial variety 'MG-03' and 'P-1972', a patented clone, and has been designated 'Dole-14'. This new variety differs from its progenitors in having higher carotenoid content, medium acidity, low fiber content, improved aroma, distinct fruit flavor and flesh colors, and a conical to cylinder shaped fruit with a long conical crown. It also shows high tolerance to NDF and less susceptibility to shell cracking. The plant is characterized by long spineless leaves with piping, that are pale to grayish green in color. When unripe, fruit shell is pale green turning to uniform yellow color when ripe, and the flesh develops a deep golden color at maturity.	2010-03-23	2008-06-26	A01H 1/02; A01H 5/08; A01H 6/22

Table B1: Biotech patent examples (Continued)

Panel B: PubChem patents

Patent Number	Abstract	Publication Date	Application Date	CPC Codes
US7081264B2	The present invention has methods for preparing a processed peanut product containing high levels of peanut hearts material, with the peanut heart material being substantially stripped of bitter taste so as to provide debittered peanut hearts of comparable taste to actual peanuts or as being flavorless without adversely affecting the taste of a foodstuff end product. The processed product includes whole or fragmented peanut hearts and peanut heart powder processed using alkaline wash, neutralization, and drying for inactivating enzymes and removing bitter flavoring components. The peanut heart materials are debittered by adjusting the pH to about 8 to about 12 with an alkali material (e.g., sodium hydroxide) to solubilize the protein content and release the bitter flavor compounds making it possible to separate such compounds by ultrafiltration. The alkali treated peanut heart material is neutralized with an acidic aqueous solution.	2006-07-25	2002-04-26	A23L 11/32; A23L 25/20; A23L 25/30
US8227409B2	Disclosed herein are fumaryl diketopiperazine (FDKP) compositions and microparticles having a specific trans isomer content of about 45% to about 65%. The FDKP microparticles can comprise a drug such as an endocrine hormone, including, peptide, including, insulin, glucagon, parathyroid hormones and the like and can be used to make a powder formulation for pulmonary delivery of the drug.	2012-07-24	2010-06-11	A61K 2121/00; A61K 31/495; A61K 38/28; A61K 9/0073; A61K 9/1635; A61P 3/00; A61P 3/04; A61P 3/10

Panel C: OECD patents

Patent Number	Abstract	Publication Date	Application Date	CPC Codes
US7247475B2	An improved method for the production of monoclonal antibodies is disclosed.	2007-07-24	2006-01-04	C07K 16/00; C07K 16/44; C12N 2510/02
US8431000B2	A biosensor for determining the concentration of an analyte in a biological sample. The biosensor comprises a support, a reference electrode or a counter electrode or both disposed on the support, a working electrode disposed on the support, the working electrode spaced apart from the other electrode or electrodes on the support, a covering layer defining a sample chamber over the electrodes, an aperture in the covering layer for receiving a sample, and at least one layer of mesh in the sample chamber between the covering layer and the electrodes. The at least one layer of mesh has coated thereon a silicone surfactant. Certain silicone surfactants are as effective as fluorinated surfactants with respect to performance of biosensors. These surfactants, when coated onto the mesh layer of the biosensor, are effective in facilitating the transport of aqueous test samples, such as blood, in the sample chamber.	2013-04-30	2012-01-05	C12Q 1/001; G01N 33/5438; Y10T 156/10

Table B2: IUCN patent examples

This table provides an example of a patent with an abstract mentioning a threatened species.

Patent Number	Abstract	Publication Date	Application Date	Species	IUCN Year
US8114445B2	Disclosed herein are dietary supplements for promoting wellness and weight loss in a subject. In one aspect, the method includes administering to a subject whom wishes to lose weight a dietary supplement containing an extract product of Salacia, an extract product of Lagerstroemea speciosa, an extract product of French maritime pine bark, an extract product of Pterocarpus marsupium, and an extract product of Syzygium cumini, said composition being administered in an amount effective to promote wellness and weight loss in the subject.	2012-02-14	2009-11-05	Pterocarpus marsupium	2017

C Use of Large Language Models for Classifying Patents

Table C1: GPT-4o mini Settings

This table provides the specification of OpenAI's GPT-4o mini in performing our classification exercise. Panel A provides the settings for identifying biotech patents. Panel B lists the settings for confirming the mention of species in patent abstracts. Panel C shows the prompt for the classification of intended commercialization of innovations.

Panel A: GPT-4o mini Settings for Identifying Bitoech Patents (PubChem)	
Item	**Content**
Model	GPT-4o mini
Temperature	0.0
Seed	1234
System message	You are an expert in evaluating whether a given patent abstract refers to a [type of input]. The [type of input] stems from the PubChem database. Use your expertise to assess whether the mention of the [type of input] refers to the protein synonym described, or to something else, and provide an accurate binary determination (1 or 0) as instructed.
User message	You are provided with a [type of input] along with a patent abstract. The [type of input] is mentioned in the abstract. Your task is to determine whether the mention of the [type of input] refers to the [type of input], or if it refers to something else. Respond with 1 if the mention refers to the [type of input], or respond with 0 if the mention does not refer to the [type of input].\n
Panel B: GPT-4o mini Settings for Confirming Species in Patents (GBIF)	
Item	**Content**
Model	GPT-4o mini
Temperature	0.0
Seed	1234
System message	You are an expert in evaluating whether a given patent abstract refers to a species based on its canonical name and kingdom. The canonical name and kingdom are derived from the classification system of the Global Biodiversity Information Facility (GBIF). Use your expertise to assess whether the mention of the species name refers to the actual species described, or to something else, and provide an accurate binary determination (1 or 0) as instructed.
User message	You are provided with the canonical name and kingdom of a species, along with a patent abstract. The canonical name of the species is mentioned in the abstract. Your task is to determine whether the mention of the species name refers to the species described by the provided canonical name and kingdom, or if it refers to something else. Respond with 1 if the mention refers to the species, or respond with 0 if the mention does not refer to the species.\n
Panel C: GPT-4o mini Settings for Classifying Intended Commercialization of Patents	
Item	**Content**
Model	GPT-4o mini
Temperature	0.0
Seed	1234
System message	You are an expert in analyzing and determining whether an invention is clearly intended for commercialization.
User message	Analyze the following patent abstract and determine whether it suggests that the invention is clearly intended for commercialization. Focus on signs of market readiness, development into a usable product, or references to scalable production. Respond with either 'Yes' or 'No'. Here is the abstract: [abstract here]