The Biodiversity Consequences of Zombie Firms: Evidence from Ecological Observations

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PRELIMINARY AND INCOMPLETE

Abstract

Using data from over 15,000 ecological sample sites in the US, we show that the proliferation of lending to zombie firms in the vicinity of these sites is associated with steeper declines in biodiversity. To ameliorate endogeneity concerns, we exploit time-series variation in the relaxation of federal bank regulation and bank risk-taking along with cross-sectional variation in bank efficiency due to staggered intrastate branch deregulation to show that biodiversity loss is attenuated in states that deregulated early. Investigating mechanisms, we find that zombie firms in the vicinity of sampling sites invest less in green technologies and produce less green innovation which, in turn, is associated with higher levels of pollution.

Key words: Zombie lending, green investment, green innovation, pollution, biodiversity

JEL Classification: G20, O30, Q57

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Biodiversity loss – the reduction in the variety of plant and animal life in the world or in a particular habit – is a defining feature of human existence and production. Recent estimates suggest that global loss in species is in the vicinity of 70% since the 1970s (World Wide Fund for Nature/Zoological Society of London, 2022) with some studies estimating that species die-off is 1,000 times more frequent today compared to when before humans walked the earth (e.g., De Vos et al., 2014) and that roughly one million animal and plant species are currently threatened with extinction, more than ever before in human history (IPBES, 2019)

While economists have for a long time been interested in understanding the implications of economic production externalities (such as air and water pollution) on the natural environment,[1] much less is known about the role that finance plays. As pointed out by Karolyi and Tobin-de la Puente (2023) and Flammer, Giroux and Heal (2025), research on biodiversity finance remains almost non-existent. Understanding the role of finance is critical for at least two reasons. First, to the extent there are externalities from finance that accelerate biodiversity loss, being able to identify and address these externalities can help slow the decline. Second, being able to frame and price the risks associated with biodiversity loss can help mobilize private capital needed to help close the "biodiversity finance gap"—estimated at $700 billion per year and represents the shortfall in financial resources required to effectively protect and restore nature (16th Conference of the Parties to the Convention on Biological Diversity (COP 16-CBD)).

The central contribution of this paper addresses former problem: We show there is a negative association between biodiversity and the proliferation of zombie firms; that is, unviable firms that survive thanks to lax credit supply by banks. The zombie firm phenomenon, and the debate around its negative and long-lasting economic and social impacts has resurfaced

[1] e.g., Weitzman, 1992, 1998; Arrow et al., 1995; Brown Jr and Shogren, 1998; Fullerton and Stavins, 1998; Heal, 2000; Brock and Xepapadeas, 2003; Liang, Rudik and Zou, 2025

amid the unprecedented public support to firms during the Covid-19 pandemic (Albuquerque and Iyer, 2024). The literature has shown that zombie lending contributed to the "lost decade" in Japan (Caballero, Hoshi, and Kashyap, 2008), and more recently to Europe's low productivity (Gouveia and Osterhold 2018, Adalet McGowan et al. 2018), low innovation (Schmidt et al. 2023), and low inflation (Acharya et al. 2024), following the sovereign debt crisis.

To operationalize our idea, we leverage a novel database known as BioTIME which contains millions of records of species counts at over 15,000 different sampling locations across the US from 1950 to 2015, and provides annual variation in sampling outcomes that reliably reflect genuine changes in underlying ecosystem conditions.[2] The coverage of taxonomic classes is impressive with the dataset including 80 percent of bird species, 40 percent of mammals, 30 percent of amphibians, 25 percent of freshwater fish, among others.

Following Liang, Rudik and Zou (2025) we use the BioTIME database to generate various quantitative measures of ecosystem conditions over time and across various locations spanning the length of the dataset. Precisely, for given location and taxonomy each year we formulate: (1) abundance, which captures the total quantity of individuals; (2) richness, which captures the total number of distinct species observed; and (3) similarity (i.e., Jaccard Similarity Index), which measures the proportion of shared species between two consecutive years of a study and reflects the stability of the species composition. We refer to these measures collectively as biodiversity, measured at the taxa-location-year frequency.

To classify publicly listed firms as zombies (i.e., highly leveraged and unprofitable) firms, we follow the accounting-based criteria set out in Albuquerque and Iyer (2024), Favara, Minoiu, and Perez (2021; 2024). Figure 1 plots the proportion of publicly listed zombie firms

[2] The database actually dates to 1903 but are sparse. Observations start to increase in 1930s but remain low until 1950.

overtime; we see growth in zombie firms following economic downturns with two notable periods where zombie firms proliferated in the US: (i) the period coinciding with timeline for national deregulation, regulatory/bank forbearance (1979-1982) and the S&L crisis (1986-1991); and (ii) the Covid-19 pandemic. Combining this classification with The National Establishment Time Series (NETS) database detailing information about the number and exact location of firms' plants we calculate the proportion of zombie plants (i.e., plants belonging to zombie firms) within a 50-mile radius of the ecological sampling location.

Our baseline model regresses measures of biodiversity on the proportion of nearby zombie plants. We show that a higher proportion of zombie plants in the vicinity of the observation location is negatively correlated with biodiversity. Moreover, this effect is concentrated in areas where local banks are more undercapitalized, consistent with the interpretation that undercapitalized banks have more incentive to keep zombie firms afloat. The economic magnitude is large, for example: in areas where banks are undercapitalized, an increase in the proportion of zombie plants by 10% is associated with roughly 1% lower biodiversity relative to the sample mean, across all three measures. These estimates control for state-level GDP per capita, and local bank competition (within 50-miles) as well as a set of location-taxon fixed effects and year fixed effects.

We examine various descriptive features of the correlation. For example, find the association between zombie firm lending and biodiversity is widespread across various taxa but the magnitude is larger in the non-bird taxonomic classes. We also examine the political determinants of this correlation and find that is stronger in years when the governor is Republican (consistent with a more pro-business stance of the Republican party), and in year immediately following gubernatorial election years during which zombie firms are more likely to proliferate given the potential political costs of local firm and bank failures (Liu and Ngo, 2014).

To aid with identification, we exploit two sources of variation. In the time series, the period 1979-82 (as we will discuss in more detail later) is widely acknowledged a significant period for interest rate and (federal) bank deregulation as well as increased bank risk taking and regulatory forbearance (Brickley and James, 1986; Saunders and Urich, 1988; Saunders, Strock and Travlos, 1990). This period was followed by the Savings and Loans crisis and a rise in the incidence of zombie firms as indicated by Figure 1. In the cross-section, this same period was also characterised by state-level deregulation of within state bank branching rules for some states but not others. The literature has shown that intrastate deregulation was associated with higher growth but that this came about because of enhanced bank efficiency (Jayaratne and Strahan, 1996). Efficient banks are less likely to make loans to zombie firms so thus we expect that, conditional on the 1979-91 period, states that deregulated (earlier) to have more efficient banks, a lower incidence of zombie firms and therefore relatively higher biodiversity. Our evidence is consistent with this conjecture: for the 1979-91 period the percentage of zombie firms headquartered within a 50-mile radius of an average observation location is significantly higher; but for states that deregulated branching laws early the proliferation of zombie firms during 1979-91 is significantly lower. Consequently, while biodiversity measures were significantly lower during 1979-91, states that deregulated earlier experienced smaller declines.

The main channel linking zombie firms to biodiversity in our paper is pollution, one of the five drivers of the biodiversity crisis (United Nations, 2022).[3] Exploiting the toxic release inventory (TRI) database, we show that plants belonging to zombie firms pollute significantly more. We argue that higher pollution by zombie firm is because they lack both the resources as well as incentives (e.g. see Acemoglu et al., 2012; Acemoglu et al., 2016) to invest in green

[3] The other drivers are invasive species, changes in land and sea use, climate change, and direct exploitation of natural resources. See Five Drivers of the Nature Crisis, United Nations Environment Program, 5 September 2023, available here: https://www.unep.org/news-and-stories/story/five-drivers-nature-crisis (accessed 29 July 2025).

technologies. Updating production and waste management processes and investment in green technologies and innovation is capital intensive (Allcott and Greenstone, 2012; Fowlie et al., 2018) and thus subject to financial frictions (Holmstrom and Tirole, 1997; Accetturo et al. 2024). The costly nature of green investment also implies that financially constrained firms might optimally choose to invest in dirty rather than clean technologies (Fang, Hsu, and Tsuo, 2025; Lanteri and Rampini, 2025) and increase pollution by firms (e.g. Levine, Lin, Wang and Xie, 2018; Xu and Kim, 2022).

Consistent with this channel, we examine green innovation and find that zombie firms are less likely to patent and produce patents of lower quality (lower citations). Aggregating to the location level, we find that as the proportion of zombie firms within 50-miles of the observation location increases, the total number and average number of patents and citations for firms within that vicinity declines significantly.

Finally, a large part of the zombie literature investigates congestion or spillover effects from zombie firms to healthy firms. The idea is that the existence of zombie firms deteriorates credit conditions and access to capital for healthy firm (see e.g., Andrews and Petroulakis, 2019; Blattner, Farinha and Bebelo, 2023) which can result in "real" spillovers in terms of employment, investment, productivity, and profit margins (Acharya et al., 2019; Acharya et al., 2022; Acharya et al., 2024; Adalet McGowan et al., 2018; Banerjee and Hofmann, 2018, 2020; Blattner, Farinha and Bebelo, 2023; Caballero et al., 2008; Schivardi et al., 2021). We investigate geographic spillovers from zombies to firms in the same industry and show that as the proportion of zombie firms increases in a given industry-location, the non-zombie peers are also associated with higher pollution and lower green innovation, especially when local banks are undercapitalized. We drill down to the plant location level and show that a higher proportion of peer firms' plants within a 50-mile radius of an observation location is associated with higher toxic emissions, lower green innovation and lower biodiversity.

Taken together, our findings demonstrate that the proliferation of zombie firms is associated with poorer biodiversity outcomes. This result comes not only from poor environmental performance of zombies but also, in part, due to credit market distortions that lowers the environmental performance of non-zombie peer firms operating in the same industry and headquartered in a similar location.

Our paper is related to the previously cited literature on the real effects of zombie lending. These papers have demonstrated that zombie lending can lead to spillovers to healthy peer firms; and the proliferation of zombies has been associated with protracted low inflation and growth, lower productivity and innovation. The closest paper to ours is the paper by Schmidt et al. (2023) who show that zombie firms are associated with lower innovation. Similarly, we show that zombie firms are associated with lower *green* innovation. We extend the analysis to link low green innovation to higher pollution by zombie firms' plants and lower biodiversity in locations in the vicinity of zombie plants.

Finally, our paper is related to the broad economics literature studying the environmental impact of production, for example, Liang, Rudik and Zou (2025) show that economic production externalities (i.e., pollution) is associated with lower biodiversity. Our paper represents one of the first to link financing to biodiversity. In particular, we show that weak banks (and weak regulators) that allow unviable firms to continue to operate is associated with greater pollution (for both zombie firms and non-zombie peer firms) lower biodiversity in ecological observation locations near zombie and peer firm plants. Our findings suggest that policies limiting regulator and bank forbearance can limit the proliferation of zombie firms and their associated negative consequences.

1 Data and Measurement

Our study will use the United States (US) banking market as a laboratory. There are two key reasons for this. First, the US banking market has experienced vast and well documented changes in market structure, mainly due to periods of regulatory and bank forbearance followed by financial crises—necessary conditions for the proliferation of zombie firms (Acharya et al., 2022)—that were orthogonal to the state of the environment. Second, our source of biodiversity data is predominantly from the US.

1.1 Zombie firms and their peers

We focus on publicly listed companies because we require accounting information to classify firms as zombies firms. We follow the criteria set out in Albuquerque and Iyer (2024), Favara, Minoiu, and Perez (2021; 2024) to identify zombie firms using annual Compustat data. Precisely, we select firms that have for at least two consecutive years: (i) an interest coverage ratio (ICR) below one, (ii) a leverage ratio above the median firm in the industry, and (iii) negative real sales growth. Figure 1 plots the proportion of publicly listed zombie firms overtime; we see growth in zombie firms following economic downturns with two notable periods where zombie firms proliferated in the US: (i) the period coinciding with timeline for national deregulation, regulatory/bank forbearance (1979-1982) and the S&L crisis (1986-1991) – the incidence of zombie firms peaked in 1982 (9.9%), 1986 (9.5%) and again in 1991 (11.1%); and (ii) the Covid-19 pandemic with 13.5% of firms being classified as zombies in 2020. The Covid spike in zombie firms was witnessed globally (Albuquerque and Iyer, 2024) and likely reflects the unprecedented policy support and easing of financing conditions worldwide. Appendix tables A1-A3 document the incidence of zombie firms overtime, across industries and across state, respectively. At the industry level, finance and insurance has that lowest incidence of zombie firms and construction has the highest. Geographically, the states

with the highest incidence of zombie firms are XXX and XXX and those with the lowest are XXX and XXX.

To study spillovers from zombies to healthy peer firms (i.e., those likely to be competing for the same bank funding), we define a peer firm as one that operates in the same industry (3 digit SIC, 2 digit NAICS?) and headquartered in the same location (state, county, within 50-miles?). This definition implies that spillovers are most likely in areas where there is industrial geographic clustering. Appendix Table A4 presents the incidence of peer firms across states and shows that XXX, XXX and XXX have the highest incidence of healthy peer firms.

1.2 Bank undercapitalization and zombie lending

The literature broadly defines zombie lending as the extension of credit by undercapitalized banks to non-viable zombie firms (e.g., Caballero et al., 2008). Undercapitalized banks have an incentive to avoid writing off existing capital because, for example: (i) they want to avoid bank capital shortfalls (Blattner et al., 2023); (ii) gambling for resurrection (Bruche and Llobet, 2014); or (iii) taking advantage of asymmetric information to offload bad borrowers to market-based lenders (Hu and Varas, 2021). In the empirical analyses, "zombie lending" is the joint occurrence of a large share of non-viable firms and under-capitalized banks in the same sector.

Following the definition under prompt corrective action, we classify banks as undercapitalized if their leverage ratio (i.e., total equity-to-assets ratio) is less than 4%. We choose this simple metric to ensure the longest and most consistent time series as regulatory definitions of capital (i.e., tier 1 vs tier 2 etc) only emerged after the introduction of the Basel Capital Accord and also subject to change overtime (i.e., what can be counted as "capital" and in which tier it should belong to). Data for bank capitalization come from Call Reports which

date back to 1976. Recent work by Hu and Varas (2021) argues that in banking relationships where the borrower has built a reputation with the bank but also has option to borrow from markets (i.e., public firms), zombie lending is inevitable because banks will chose to rollover debt even after privately learning bad news (that is unknown to the market). The literature has also shown that proximity between banks and borrowers fosters relationships and reduces the cost of information production for banks (e.g., Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). Therefore, to capture distance-based lending relationships, we construct a firm-level measure of bank undercapitalization that varies with geography.[4] Specifically, we exploit branch location data from the FDIC Summary of Deposits (SoD, available from 1994), to create a variable *Undercap*(*Branch*) equal to the proportion of undercapitalized banks (leverage ratio < 4%) with operations (i.e., branches) within a 50-mile radius of firm headquarters, weighted by the size of the bank (total assets). We choose to centre on firm headquarters because firm financing decisions are typically carried out at the headquarter-level (as opposed to at the plant-level).

Since relying on branch location information limits our sample start to 1994, we create an alternative measure based on the headquarter location of banks *Undercap*(*HQ*) which is equal to the proportion of undercapitalized banks with headquarters in the same state as the focal firm's headquarters, weighted by the size of the bank. We can calculate this second measure starting in 1976.

Table 1 presents the summary statistics for *Undercap*(*Branch*) and *Undercap*(*HQ*). We see that the mean of *Undercap*(*Branch*) and *Undercap*(*HQ*) is XXX and XXX, with a standard deviations of XXX and XXX, respecitively. Figure 2 plots firm-level exposure to undercapitalized banks overtime using the two measures. We can see that the two measures

[4] Though distance in lending is arguably less important in this day and age with the internet, mobile phones and the like (Petersen and Rajan, 2002) recent papers show that lending remains very local (Nguyen, 2019; Blickle, 2022; Adams et al., 2023).

pick up similar time trends: bank undercapitalization is countercyclical, rising during downturns and falling during periods of strong growth. The pattern largely mirrors that of the prevalence of zombie firms shown in Figure 1.

1.3 Biodiversity

A major obstacle for empirical research has been the lack of largescale data on species observations (Geijzendorffer et al., 2016; Konig et al., 2019). Existing datasets are limited in that they commonly fall into two categories: those that provide only cross-sectional information on the geographic extent of species, such as the International Union for Conservation of Red List of Threatened Species; or those that provide panel data for only a *single* taxonomic class, such as the US Geological Survey's (USGS) North American Breeding Bird Survey Dataset.

We make progress by leveraging a new and underutilised main dataset known as BioTIME. The BioTIME database provides as close to an ecological panel dataset as one could hope for; for over 15,000 sampling locations in the US since 1950. This database is constructed by compiling and merging hundreds of individual ecological studies that maintain longitudinal information on the counts or biomass of relevant species (Dornelas et al., 2018; Blowes et al., 2019). The studies chosen for inclusion are consistent in their sampling protocols within each sampling location over time resulting in an "assemblage time series" which provides annual variation in sampling outcomes that reliably reflect genuine changes in underlying ecosystem conditions. Appendix tables A5-A7 show the distribution of observations, taxa count, location count and years of coverage by taxa, by state and by year, respectively. We see that the taxa with the highest observation counts are XXX and XXX, and states of Montana and Idaho have the largest number of observation locations with 10,812 and 2,037, respectively.

We follow Ling, Rudik and Zou (2025) and exclude marine ecosystem studies, which often take place tens or hundreds of miles offshore and, thus, are difficult to link to measures

of local production and pollution. We also focus on studies that report species abundance (i.e., counts of individuals), and exclude studies that only report total species biomass or only an indicator for species presence (less than 1% of samples) so that we have a unified measure of abundance. We aggregate raw species sampling observations data to the location (i) -taxon (j) -year (t) level and to calculate three measures that capture biodiversity. The included taxa are birds, fish, mammals, terrestrial invertebrates, freshwater invertebrates, terrestrial plants, and freshwater plants.[5]

Declines in the three measures are indicative of deteriorating biodiversity outcomes because they indicate reductions in populations and diversity and increases in the instability of species composition.

1. Abundance ($A_{i,j,t}$) is the natural logarithm of one plus the total quantity of individuals. Abundance simply measures the pure quantity of individuals observed and is agnostic about the types of species in the sample. It is worth noting that virtually all studies examine closely related species that fall in the same taxon group. Therefore, abundance is never measured by combining distant species, such as birds and fish.
2. Richness ($R_{i,j,t}$) is the natural logarithm of one plus the total number of distinct species observed; This metric is agnostic about the composition of species or how the composition of species has changed. For example, if there is an equal loss of native species and introduction of invasive species, species richness will not change despite changes in the composition of the ecosystem.
1. Jaccard Similarity Index is a ratio of the number of species in taxon j present at location i in both times t and t+1 relative to the number of species present in

[5] Our raw sample also includes 30 reptile observations at one location, and one observation at a second location. Given how little data we have on reptiles we drop them from the sample.

either of the two times; thus, it provides a measure of compositional changes in the ecosystem. The index is bounded between zero and one with lower values indicating some combination of loss of species, or the introduction of new species between times t and t+1. In the limiting case where the index is equal to zero, there are no common species in times t and t+1; on the other hand, a similarity index value of one indicates that the exact same set of species is present in times t and t+1 and there is no species turnover. Formally, let $S_{i,j,t}$ be the set of species at some location i, in taxon j, at time t and n(.) denote the cardinality of a set, then the Jaccard Similarity Index is given by

$$J_{i,j,t} = \frac{n(S_{i,j,t+1} \cap S_{i,j,t})}{n(S_{i,j,t+1} \cup S_{i,j,t})}$$

Ling, Rudik and Zou (2025) discuss the potential sources of bias in the BioTime data and demonstrate that there is substantial year-on-year variation in these measures and that the vast majority of observations fall within observations fall within plus or minus one log unit range. Table 1 presents summary statistics of these measures. The mean (standard deviation) for Abundance, Richness and Jaccard Similarity Index are 3.29 (1.97), 2.28 (0.97) and 0.46 (0.25). The most abundant taxon is freshwater invertebrates, and the taxon with the most number of species (Richness) is freshwater plants, whereas the most stable taxa is amphibians (highest Jaccard Similarity Index).

1.4 Production, pollution and green investment

Our measures of production will rely on The National Establishment Time Series (NETS), which is a private sector source of U.S. business microdata. NETS data have been used in a number of studies (e.g. Neumark et al., 2005). The source data for NETS are collected

by Dunn & Bradstreet (D&B). The data provide information about the number of plants in a certain area, the size of the plant (number of employees and revenue) and exact location.

We use the establishment name and location in NETS to match to the Environmental Protection Agency Toxic Releases Inventory (TRI) program database—our main source of information on facility-level toxic release. The Emergency Planning and Community Right-to-Know Act requires reporting to the TRI program if facilities with ten or more full-time employees meet the criteria on industry sector and release any toxic substance in excess of the reporting threshold via air, water, land, or underground injection. With a total of 767 chemicals in 33 chemical categories, the TRI program covers all chemicals that cause cancer or other chronic/acute diseases and have significant adverse effects on the environment. The TRI program provides information on facilities and their parent companies, so we are able to aggregate annual toxic releases at the parent-company level. We can then match the annual total toxic releases data with Compustat and CRSP identifiers following the matching procedure in Xu and Kim (2022). Table 1 shows that the average firm has 79 plants in 38 different counties and 10 different states. Total emissions at the firm level is on average 299783 pounds with a large standard deviation of 4083063 which in part reflects differences in pollution intensity at the industry level. On site emissions represent 81% of total emissions.

We focus on corporate innovation rather than traditional corporate investments because unlike capital or R&D investment, patent applications provide information on technology classes, which can be used to determine a firm's environment-friendly investment activity following the Organization for Economic Co-operation and Development (OECD) guidelines. Our data source of green innovation is the United States Patent and Trademark Office (USPTO) patent database.[6] The patent database provides information on the identity of patent recipients, the number of citations received by each patent, application dates, grant dates, the patent's

[6]

primary and secondary technological classes, etc. We label a patent as green if any of its International Patent Classification system (IPC) or Cooperative Patent Classification system (CPC) is categorized as environment-friendly. Green patents usually refer to technologies related to emission abatement, renewable energy, and energy storage. Our classification of patents closely follows the OECD guidelines with a few necessary modifications that are standard in this literature (Hascic and Migotto, 2015; Cohen et al., 2022). For example, we define all patents under the Y02 classification as green patents, because this category includes "[t]echnologies or applications for mitigation or adaptation against climate change." We read descriptions of technology classes from Hascic and Migotto (2015) and search websites maintained by World Intellectual Property Organization (WIPO) and CPC to ensure consistency with CPC/IPC classes. During January 1, 1963—December 31, 2019, we find a total of 162,839 green patents granted to 2,390 unique firms. Table 1 shows that the average firm produces 0.8 patents and XXX citations over a three year period.

2 Empirical Approach and Baseline Results

We begin with correlational evidence using panel regressions where our dependent variable of interest are the three biodiversity measures: Abundance, Richness and the Jaccard Similarity Index. The unit of observation is at the i (= ecological sampling location) – j (= taxon) – t (= year) level. For each location-year (i, t) we compute the exposure of the sample location to zombie lending (i.e., the joint effects of zombie firms and undercapitalized banks likely to lend to these firms). We have two approaches for this.

First, in primary approach we leverage firms' plant location from NETS and bank branch location from FDIC SoD to measure exposure to zombie lending, this approach provides us a more accurate measurement of the exposure of sampling locations to zombie lending but limits our sample to start from 1994. Specifically, we denote each plant of a zombie

firm a zombie plant, then we calculate the proportion of zombie plants within a 50-mile radius of the ecological sampling location *i*, denoted %*Zombie Plants*. We chose a tight radius around the sampling location for consistency with our proposed mechanism we investigate later: That zombie firms pollute more.

Since the role of firm headquarters is to allocate capital to and other resources to its plants (Giroud and Mueller, 2015; 2019) we assume that each plant belonging to the same is equally exposed to the same degree of bank undercapitalization as firm headquarters, given by the variable *Undercap*(*Branch*) described above. Next, for any given sampling location *i*, plants belonging to different firms with headquarters are differentially exposure to bank undercapitalization. Thus to measure the location *i*'s exposure to bank undercapitalization we calculate mean *Undercap*(*Branch*) across all plants within a 50-mile radius of location *i*, denoted, $\overline{Undercap(Branch)}$. Our baseline regression is:

$$\begin{aligned} Biodiversity_{i,j,t} = \ & \alpha + \delta_1 \%Zombie\ Plants_{i,t} + \delta_2 \overline{Undercap(Branch)}_{i,t} \\ & + \delta_3 \%Zombie\ Plants_{i,t} \times \overline{Undercap(Branch)}_{i,t} \\ & + \delta_4 \mathrm{GDP}_{\mathrm{s,t}} + \emptyset_{i,j} + \emptyset_t + \in_{i,j,t} \end{aligned} \quad (1)$$

Where *GDP* is state-level GDP per capital; $\emptyset_{i,j}$ location-taxon fixed-effects; $\emptyset_t$ is year fixed-effects, which can also vary by state or by county depending on the specification; and $\in_{i,j,t}$ is the error term. Our central hypothesis is that zombie firms and zombie lending are negatively associated with biodiversity, implying that $\delta_1 < 0$ and $\delta_3 < 0$.

In our second approach, we do not use NETS nor the FDIC SoD databases and extend our analysis back to 1976. Our analysis replaces %*Zombie Plants* with %*Zombie Firms* which is the proportion of zombie firms headquartered within a 50-mile radius of the sampling location *i*. Similarly, we replace $\overline{Undercap(Branch)}$ with *Undercap*(*HQ*) which is the

exposure of firms within the vicinity of the sampling location to undercapitalized banks. Since not all production is carried our at headquarters, this approach introduces measurement error. However, the trade-off is that it allows us to investigate a much longer time series.

2.1 Baseline Results

Table 2 presents our results from our baseline analysis using our post-1994 sample. Since almost 70% of our observations come from "birds" we run our analysis on the full sample as well as on a sample excluding birds to ensure that our results are not driven by any one taxon. Columns 1-3 present our results for all taxa whereas Columns 4-6 exclude birds. Consistent with Ling, Rudik and Zou (2025) we find that there is a strong and negative relation between GDP per capita and biodiversity. Next, our central hypothesis is that zombie lending is negatively associated with biodiversity; consistent with this, the interaction term $\%Zombie\ Plants_{i,t} \times \overline{Undercap(Branch)}_{i,t}$ is negative and significant is all but one of the six columns (Column 6) where the coefficient is negative but imprecisely estimated. The point estimates are also of similar magnitudes between the full sample and the sample excluding birds.

Focusing on the estimates from the full sample (Columns 1-3), the point estimates imply that in areas where local banks are undercapitalized a rise in the percentage of zombie plants by 10 percentage points (equivalent to the typical rise during and following major economic/financial) is associated with about a 1% decline in biodiversity relative to the sample mean, or 1.5% decline relative to the sample standard deviation, for all three measures. For example, the coefficient estimate on the interaction term in Column 1 is -0.318 implies that when $\overline{Undercap(Branch)}_{i,t} = 1$, an increase in $\%Zombie\ Plants_{i,t} = 0.1$ is associated with a 0.0318 log unit decrease in abundance. When compared to the sample mean (standard deviation) of 3.29 (1.97) the reduction is equivalent to a 1% (1.6%).

2.2 Extended Sample

TO DO: Extended sample from 1976

3 Identification

The negative association between zombie lending and biodiversity may be subject to endogeneity concerns, due to omitted variable bias, measurement error or reverse causality. Since "zombie lending" is defined as the joint occurrence of a large share of non-viable firms and under-capitalized banks in the same sector or location, our first approach to aid with identification leverages a historical episode associated with lax lending standards, regulatory forbearance and the proliferation of zombie firms.

Specifically, the period 1979-82 is widely acknowledged a significant period for interest rate and (federal) bank deregulation as well as increased bank risk taking and regulatory forbearance (Brickley and James, 1986; Saunders and Urich, 1988; Saunders, Strock and Travlos, 1990). First, between October 1979 and October 1982, the Federal Reserve changed its monetary policy operating targets away from interest rates toward non-borrowed reserve which led to a considerable increase in interest rate volatility (See Saunders and Urich, 1988) Moreover, in 1980 the Depository Institutions Deregulation and Monetary Control Act **(**DIDMCA**)** was passed that deregulated interest rate ceilings on deposits and expanded the powers of the Federal Reserve. This was followed in 1982 with the Garn-St. Germain Act, deregulated savings and loan associations (e.g., permitted to switch chartering authority, broadened the scope of investment activities) and allowed banks to provide adjustable-rate mortgage loans. This period was followed by the Savings and Loans crisis where over 1000 thrifts failed and a rise in the incidence of zombie firms as indicated by Figure 1. We therefore

characterise the 1979-1991 period as one characterised with lax lending and regulatory standard and a proliferation of zombies.

To aid with identification, we exploit a second source of variation: The timing of intra-state branching deregulation. Prior literature has shown that early deregulation was more efficient banks and higher economic growth (Jayaratne and Strahan, 1996). In particular, Jayaratne and Strahan (1996) show that deregulation resulted in efficient banks acquiring inefficient banks within the same state and document that banks' profitability improved due to decreased non-interest costs and, crucially, reduced loan losses. Consistent with this, Chava, Oettl, Subramanian, and Subramanian (2013) show that intrastate deregulation reduced lending to riskier firms (particularly young and small). Our prediction is that, although the 1979-91 period is characterised nationally as a period of lax lending standards, states that deregulated intrastate branching laws earlier experienced improved bank efficiency, standards and profitability, in part, via reduced zombie lending.

Table 3 validates our approach on our extended sample beginning in 1964. For each observation location in BioTime, we calculate the proportion of zombie firms headquartered within 50-miles of the sampling location (i.e. %*Zombie Firm*). In Column 1 we regress %*Zombie Firm* on an indictor equal to 1 for all state-years after interstate branching deregulation (i.e. *INTRA*) controlling for state GDP per capita as well as location and year fixed-effects. As expected, we see as strong negative association between *INTRA* and the proportion of zombie firms in the vicinity of sampling sites. In Column 2 we add the interaction between *INTRA* and an indicator equal to 1 for the years 1979-1991 (the level effect of the time period dummy is absorbed by year fixed-effects). Our prediction is that although 1979-1991 is a period in which zombie firms proliferated, in areas that deregulated earlier and banks became more efficient, the proliferation of zombie firms and zombie lending was attenuated.

Consistent with this expectation, we see that the coefficient on the interaction term *INTRA* x *Year79_91* is negative and significant.

We next link these two sources of variation to biodiversity by regressing our biodiversity measures on *INTRA* and the interaction term *INTRA×Year79_91* controlling for state-level GDP per capita as well as year and location-taxa fixed effects. Our discussion and findings show that states that deregulated intrastate branching earlier attenuated the proliferation of zombie lending during 1979-1991, thus we expect biodiversity to be relatively higher in these states during 1979-1991. The results presented in Table 4 confirm our prediction: We see that for the non-bird taxa the coefficient on *INTRA×Year79_91* is positive and significant across all three measures of biodiversity. Interestingly, the coefficient on *INTRA* is negative and significant suggesting that early deregulation is associated with relatively poorer biodiversity outcomes in years outside of 1979-1991. This result is consistent with the findings of Jayaratne and Strahan (1996) who show that intrastate deregulation lead to higher economic growth. Indeed, in Table 4, the coefficient on GDP per capita is no longer significant (and even positive in some cases) suggesting possible collinearity between *INTRA* and GDP per capita. We note that we find no supporting evidence in the sample including birds which is largely due to the fact that the bird taxon, which makes up the majority of observations, has a higher degree of measurement error (all three measures of biodiversity have very large standard deviations compared to their own mean and compared to other taxa, see Table 1) and since our identification comes from coarse state-level variation the point estimates in Columns 1-3 of Table 4 are imprecisely estimated.

Overall, our evidence in this section is consistent with our baseline findings presented in Section 2. Zombie lending is associated with poorer biodiversity outcomes. In the next section we investigate the mechanisms behind this finding.

4 Economic Channels

The main channel linking zombie firms to biodiversity in our paper is pollution, one of the five drivers of the biodiversity crisis (United Nations, 2022). Zombie firms are defined by their inability to cover interest expenses with profits, so their main goal is to remain operational, leading them to focus on short-term survival rather than long-term growth. This short-term focus may lead them to neglect investing in pollution abatement technologies which are capital intensive (Allcott and Greenstone, 2012; Fowlie et al., 2018; Fang, Hsu, and Tsuo, 2025; Lanteri and Rampini, 2025)); in research and development and innovation (Schmidt et al., 2023), especially in green technologies; or simply to take shortcuts when it comes to toxic waste and pollution management. That is, zombie firms pollute more because they lack both the resources as well as incentives (e.g. see Acemoglu et al., 2012; Acemoglu et al., 2016) to invest in green technologies.

In this section, we investigate whether zombie firms are less likely to invest in green technologies and pollute more. We present evidence at the firm as well as the plant level, and then link these outcomes to the ecological sampling locations.

4.1 Firm level evidence

Green Investment/Innovation – TO DO, look into Refinitiv ESG, USPTO

Pollution – TO DO, look into TRI, Refinitiv ESG

To examine the association between "zombieness" and firm green investment and pollution we run the following regression at the firm-year level.

$$y_{f,t} = \alpha + \delta_1 Zombie_{f,t} + \delta_2 Undercap(Branch)_{f,t}$$

$$+\delta_3 Zombie_{f,t} \times Undercap(Branch)_{f,t}$$

$$+\boldsymbol{\delta}' \boldsymbol{X}_{\boldsymbol{f,t-1}} + \emptyset_f + \emptyset_t + \in_{f,t} \quad (2)$$

where $y_{f,t}$ is the dependent variable (either green investment, innovation or pollution) and $Zombie_{f,t}$ take one of two forms: (i) an indicator equal to one if firm *f* is identified as a zombie firm in year *t*, and zero otherwise; or (ii) recognising that zombification is a gradual process, we place firm *f* in year *t* into a decile rank according the three factors used to define a zombie firm outlined in section 1.1.[7] $Undercap(Branch)_{f,t}$ is a continuous variable described above indicating the proportion undercapitalized banks active within the vicinity of firms' headquarters, $\boldsymbol{X}_{\boldsymbol{f,t-1}}$ is a vector of lagged firm controls, $\emptyset_f$ is a firm fixed effect and $\emptyset_t$ is a time fixed effect which varies by year or by industry-year or by HQ state-year, depending on the specification.

4.2 Plant level evidence

The toxic release inventory (TRI) database provides plant level information about toxic emissions and waste management. Since plant level observations increase the accuracy of linking outcomes to the observation location, we confirm that plants belonging to zombie firms pollute more. Plant level analysis also improves our identification as we are able to include plant-level fixed effects which accounts for time-persistent factors at the plant-level, such as production location related factors which we cannot control for at the firm level. We are also able to alter our time fixed effects to vary by plant location-year (e.g., county- or state-by-year), meaning we are comparing only neighbouring plants in the same location and year. We run

[7] Precisely, we calculate for each firm year *z* = (interest coverage ratio + sales growth – leverage ratio) and then place firms into a reverse decile rank according to *z* such that a higher rank represents a greater degree of zombieness.

regressions similar to Equation (2) assuming all plants inherit the same degree of zombieness from headquarters.

Table 5 presents the results from plant level analysis using the zombie decile rank as the main independent variable. In our baseline regression, we control for firm size and the book-to-market as well as year and industry fixed effects. The dependent variable for Columns 1 through 3 are total releases, on-site releases and off-site releases, respectively. The results show across three columns that increasing zombieness is associated with higher toxic releases. From Column 1, an increase in the zombie decile ranking is associated with a 12.5% increase in total toxic releases.

In the remaining columns, we introduce the interaction with $Undercap(Branch)_{f,t}$ and vary the fixed effects. TO DO.

4.3 Sampling location evidence

In this section, we link firm and plant level outcomes for green investment and pollution to the ecological sampling location. Recall from Equation (1) that we linked $\%Zombie\ Plants_{i,t}$ in the vicinity of the sampling location to biodiversity outcomes, in a similar fashion we assess how green investment and pollution of firms operating in the local area varies with $\%Zombie\ Plants_{i,t}$ in the same area in the following regression:

$$y_{i,t} = \alpha + \delta_1 \%Zombie\ Plants_{i,t} + \delta_2 \overline{Undercap(Branch)}_{i,t} + \delta_3 \%Zombie\ Plants_{i,t} \times \overline{Undercap(Branch)}_{i,t} + \delta_4 \mathrm{GDP}_{s,t} + \emptyset_i + \emptyset_t + \in_{i,t} \quad (3)$$

Where $y_{i,t}$ is either the mean or total of our investment measure or pollution measure. We begin with green innovation and report the results in Table 6. Here $y_{i,t}$ is the total number (top

panel) and mean number (bottom panel) of patents and citations in years t+1 to t+3. Consistently across all columns, we see that $\%Zombie\ Plants_{i,t}$ is negatively correlated with green innovation of firms with plants operating in the local area of the sampling location.

Pollution – TO DO

5 Do spillovers to peer firms exist?

A debate in the literature is whether zombie firms create congestion or distortionary effects in credit markets. Some recent evidence (see e.g., Andrews and Petroulakis, 2019; Blattner, Farinha and Bebelo, 2023; Schmidt et al., 2023) while others argue that the performance of healthy firms remains unaffected (e.g. Schivardi et al, 2022).

In this final section, we investigate whether spillovers from zombies to healthy firms also contribute negatively to biodiversity. Section 1.1 defines a peer firm as one that operates in the same industry and headquartered in the same location as the focal zombie firm. We leverage plant level data to perform our tests, assuming that any credit distortions that occur at headquarters is transmitted equally to all operating plants. We then calculate the proportion of peer firm plants within a 50-mile radius of location *i* in year *t*, $\%Peer\ Plants_{i,t}$. The benefit of this approach is it enables us to better disentangle the effects of zombies versus peers, because peer firm plants are not located in the exact locations as zombie firm plants: The correlation between location of zombie plants and location of peer firm plants is only XXX.

We add $\%Peer\ Plants_{i,t}$ along with its interaction with $\overline{Undercap(Branch)}_{i,t}$ into Equation (1) and run the following regression:

$$Biodiversity_{i,j,t} = \alpha + \delta_1 \%Zombie\ Plants_{i,t} + \delta_2 \overline{Undercap(Branch)}_{i,t}$$

$$+\delta_3 \%Zombie\ Plants_{i,t} \times \overline{Undercap(Branch)}_{i,t}$$

$$\delta_4 \%Peer\ Plants_{i,t} + \delta_2 \overline{Undercap(Branch)}_{i,t}$$

$$+\delta_5 \%Peer\ Plants_{i,t} \times \overline{Undercap(Branch)}_{i,t}$$

$$+\delta_6 \mathrm{GDP}_{s,t} + \emptyset_{i,j} + \emptyset_t + \in_{i,j,t} \quad (4)$$

TO DO.

6 Conclusion

Using ecological panel data from BioTIME covering more than 15,000 sampling sites across the United States (1950–2015), we examine how the prevalence of zombie firms—unviable companies kept alive through lax credit—relates to biodiversity outcomes. Leveraging plant locations (NETS), bank undercapitalization around firm headquarters (FDIC SoD and Call Reports), and proximity to ecological sampling sites, we document that areas with a higher share of zombie plants experience poorer biodiversity outcomes, especially where local banks are more undercapitalized. Building identification, we exploit the 1979–1991 episode of regulatory forbearance and risk taking and cross-state variation in intrastate branch deregulation timing: states that deregulated earlier exhibit an attenuation of zombie proliferation during 1979–1991 and correspondingly smaller biodiversity losses. Mechanistically, zombie firms appear to pollute more and innovate less in green technologies: plant-level toxic releases increase with zombieness and local green patenting declines as the share of zombie plants rises. Overall, our evidence links weak bank behavior and zombie lending to degraded environmental performance and biodiversity in nearby ecosystems.

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Figure 1 Proportion of publicly listed zombie firms

This figure plots the proportion of publicly listed firms that are classified as zombie (i.e., highly leveraged and unprofitable) firms using the criteria set out in Albuquerque and Iyer (2024), Favara, Minoiu, and Perez (2021; 2024). More precisely, we require that zombie firms have leverage above the sample annual median, interest coverage ratio (ICR) below one, and negative real sales growth over the preceding three years.

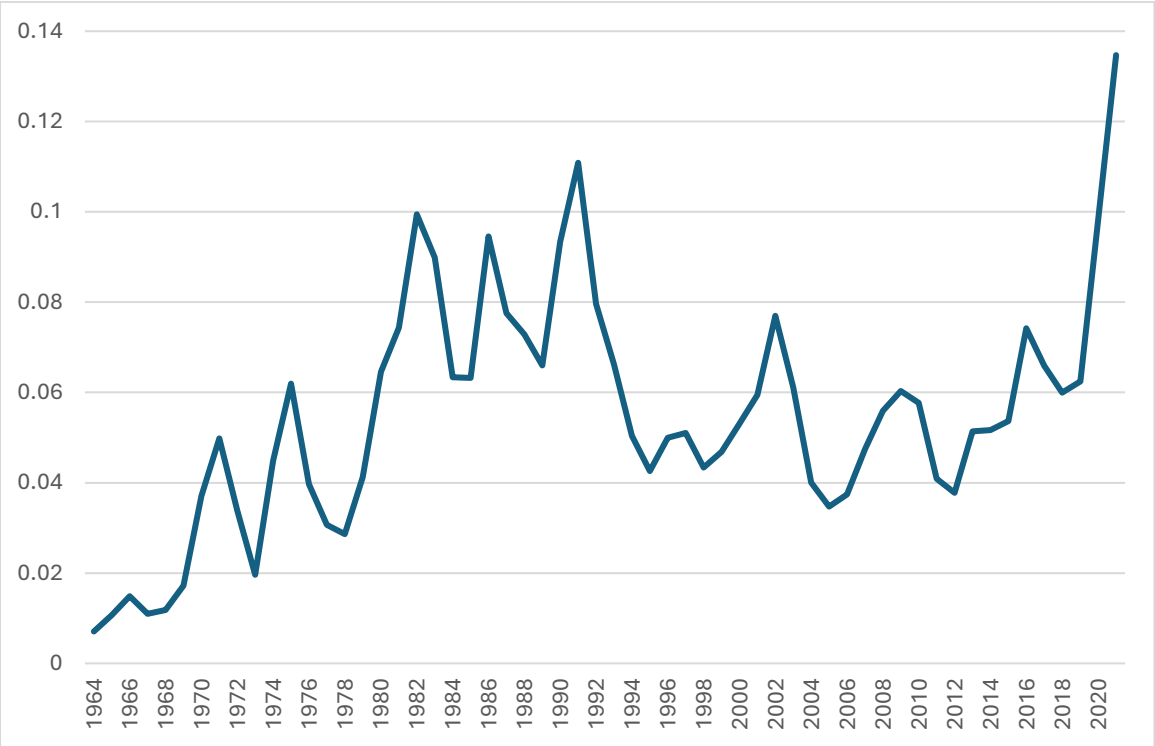


Table 1 Summary statistics

This table presents summary statistics for the key biodiversity measures used in the study. The data are organised at the taxa-location-year level and the sample period is 1950-2015. Our main variables of interest are: (i) Abundance ($A_{i,j,t}$) is the natural logarithm of one plus the total quantity of individuals; (ii) Richness ($R_{i,j,t}$) is the natural logarithm of one plus the total number of distinct species observed; and (iii) Jaccard Similarity Index ($J_{i,j,t}$) is a ratio of the number of species in taxon j present at location i in both times t and t+1 relative to the number of species present in either of the two times. The index is bounded between zero and one with lower values indicating some combination of loss of species, or the introduction of new species between times t and t+1.

Panel A	N	Mean	Std Dev	Minimum	25th Pctl	Median	75th Pctl	Maximum
Firm-level								
zombie indicator	133012	0.06	0.24	0.00	0.00	0.00	0.00	1.00
zombie rank	133012	-5.81	1.58	-9.00	-7.00	-6.00	-4.67	0.00
Bank Undercapitalization	63676	0.05	0.44	0.00	0.00	0.00	0.00	15.57
Bank HHI	63557	0.17	0.10	0.03	0.10	0.14	0.20	1.00
Sales growth	133012	0.55	32.48	-48.87	-0.05	0.05	0.18	8703.76
Leverage	133012	0.30	0.25	0.00	0.08	0.25	0.47	1.00
Low_ICR	133012	0.31	0.46	0.00	0.00	0.00	1.00	1.00
# of plants	77655	79.40	317.55	0.00	3.00	10.00	39.00	9179.00
# coutnies operating in	77655	37.68	105.64	0.00	2.00	6.00	25.00	1904.00
# states operating in	77655	9.67	12.00	0.00	1.00	4.00	13.00	53.00
total pollution (TRI)	88343	299783.98	4083063.28	0.00	0.00	0.00	0.00	542043676.00
on-site pollution (TRI)	88343	244319.30	3693587.10	0.00	0.00	0.00	0.00	541633396.00
off-site pollution (TRI)	88343	55464.68	1234641.50	0.00	0.00	0.00	0.00	99539766.33
# of green patents [t-4, t]	127399	0.67	6.75	0.00	0.00	0.00	0.00	574.00
# of green patents [t+1, t+3]	127399	0.80	8.84	0.00	0.00	0.00	0.00	1092.00
Plant-level								
zombie indicator	6318684	0.05	0.21	0.00	0.00	0.00	0.00	1.00
zombie rank	6197492	-5.65	1.29	-9.00	-6.67	-5.67	-4.67	0.00
Bank Undercapitalization	11823929	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bank HHI	5621164	0.00	0.00	0.00	0.00	0.00	0.00	0.00
total pollution (TRI)	13095233	2987.53	327830.52	0.00	0.00	0.00	0.00	343995350.00
on-site pollution (TRI)	13095233	2622.36	323213.16	0.00	0.00	0.00	0.00	343995348.00
off-site pollution (TRI)	13095233	365.17	49380.38	0.00	0.00	0.00	0.00	43403773.10

Taxa-location level								
number of zombie plants in 50 miles	60,719	0.361	1.016	0	0	0	0	26
% zombie plants in 50 miles	60,719	0.865	4.074	0	0	0	0	100
undercapitalization of banks in 50 miles	29,863	0.0198	0.295	0	0	0	0	19.52
pollution of plants in 50 miles	60,719	1.677e+06	5.879e+06	0	41.27	50,106	612,100	1.148e+08
Average # of green patents [t-4, t] in 50 miles	60,719	2.102	3.633	0	0	0.167	3.275	44.44
Average # of green patents [t+1, t+3] in 50 miles	60,719	1.682	3.207	0	0	0.100	2.188	39.81
Bank HHI for plants in 50 miles	51,643	4,447	2,455	7.142	2,316	4,054	6,026	10,000
Biodiversity								
Abundance	67189	38686.84	1223817.23	0	7	13	35	103791023
Richness	67189	15.506958	19.9552261	1	4	8	13	417
Ln(Abundance+1)	67189	3.2871544	1.9699931	0	2.0794415	2.6390573	3.5835189	18.4578901
Ln(Richness+1)	67189	2.2791831	0.9713686	0.6931472	1.6094379	2.1972246	2.6390573	6.0354814
Jaccard_sim_alt	47550	0.4638945	0.2498543	0.025641	0.25	0.4	0.6981132	1

Panel B	Abundance		Richness		Jaccard_sim_alt	
Biodiversity by TAXA	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Amphibians	2563.20	2556.61	7.27	2.53	0.94	0.10
Birds	216.80	1996.54	18.41	20.46	0.44	0.24
Fish	1404.77	6329.64	16.07	8.50	0.70	0.13
Freshwater invertebrates	4087492.79	12214077.82	21.37	14.35	0.71	0.16
Freshwater plants	2747856.72	1193869.22	83.87	11.56	0.47	0.04
Mammals	21.47	174.89	1.93	1.97	0.55	0.27
Terrestrial invertebrates	52.88	418.32	4.35	11.07	0.48	0.21
Terrestrial plants	1146.71	7969.38	10.69	28.57	0.68	0.30

Table 2 Zombie firms and biodiversity

This table presents the baseline results from estimating Equation (2) for our main sample covering 1996-2015. The dependent variables are (i) Abundance ($A_{i,j,t}$) is the natural logarithm of one plus the total quantity of individuals; (ii) Richness ($R_{i,j,t}$) is the natural logarithm of one plus the total number of distinct species observed; and (iii) Jaccard Similarity Index ($J_{i,j,t}$) which captures the stability of a given taxa-location. The independent variables of interest are (i) *Zombie_Plant_Pct* which is the percentage of zombie plants (i.e., plants that are owned and operated by zombie firms) within a 50-mile radius of the observation location; (ii) *Under_Capitalized* captures the proportion of undercapitalized banks (equity-to-assets ratio < 4%) with operations (i.e., branches) within a 50-mile radius of the observation location, weighed by the deposit share of the banks in that area; and (iii) the interaction of *Zombie_Plant_Pct* and *Under_Capitalized*. We control for *GDP_PC* which is state-level gross domestic product per capita. Significance levels of 10, 5, and 1 percent are represented by *, **, and *** respectively.

	All Taxa			Non-bird Taxa		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var=	$A_{i,j,t}$	$R_{i,j,t}$	$J_{i,j,t}$	$A_{i,j,t}$	$R_{i,j,t}$	$J_{i,j,t}$
Zombie_Plant_Pct	-0.005	-0.004***	-0.001**	-0.126**	-0.036**	-0.004
	(-1.366)	(-3.880)	(-2.206)	(-2.637)	(-2.853)	(-0.578)
Zombie_Plant_Pct x Under_Capitalized_VW	-0.318**	-0.150**	-0.037*	-0.253**	-0.117**	-0.039
	(-2.085)	(-2.446)	(-1.906)	(-2.268)	(-2.475)	(-1.490)
Under_Capitalized_VW	-0.075***	-0.017***	-0.003*	-0.111***	-0.021***	-0.004**
	(-2.872)	(-3.675)	(-1.870)	(-3.365)	(-3.913)	(-2.388)
GDP_PC	-1.524***	-0.825***	-0.102	-1.384***	-1.152***	-0.059
	(-3.213)	(-3.282)	(-1.023)	(-3.314)	(-8.258)	(-0.355)
TAXA Location FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
State Clustering	Y	Y	Y	Y	Y	Y
Observations	32,149	32,149	24,414	10,773	10,773	7,586
Adjusted R-squared	0.944	0.920	0.649	0.922	0.847	0.288

Table 3 The proliferation of zombie firms: Evidence from historical events

This table presents the baseline results from estimating Equation (3) for our extended sample covering 1964-2015. The dependent variable is *Zombie_Firm_Pct* which is the percentage of zombie firms headquartered in a zip code within 50-miles around the observation location. The independent variables of interest are (i) *INTRA* which is an indicator equal 1 for all state-years after when a state removes intra-state branching regulations; (ii) *Year79_91* is an indicator for the years from 1979 to 1991 a period associated with lax regulatory enforcement and lending standards as well as the savings and loans crisis; (iii) the interaction of *INTRA* and *Year79_91*; (iv) *Trend* which is a linear time trend. We control for *GDP_PC* which is state-level gross domestic product per capita. Significance levels of 10, 5, and 1 percent are represented by *, **, and *** respectively.

>=1964	(1)	(2)	(3)
Dep Var=		*Zombie_Firm_Pct*	
INTRA	-2.375***	-1.679***	-0.057
	(-5.035)	(-4.340)	(-0.050)
INTRA x Year79_91		-1.380***	-0.242
		(-3.400)	(-0.416)
Year79_91			4.380***
			(7.428)
Trend			0.257***
			(2.749)
GDP_PC	-9.551*	-9.654*	-4.131***
	(-1.769)	(-1.762)	(-3.407)
Location FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
State Clustering	Yes	Yes	Yes
Observations	814,161	814,161	814,161
Adjusted R-squared	0.114	0.114	0.0412

Table 4 Zombie firms and biodiversity: Evidence from historical events

This table presents the baseline results from estimating Equation (2) for our extended sample covering 1950-2015. The dependent variables are (i) Abundance ($A_{i,j,t}$) is the natural logarithm of one plus the total quantity of individuals; (ii) Richness ($R_{i,j,t}$) is the natural logarithm of one plus the total number of distinct species observed; and (iii) Jaccard Similarity Index ($J_{i,j,t}$) which captures the stability of a given taxa-location. The independent variables of interest are (i) *Zombie_Plant_Pct* which is the percentage of zombie plants (i.e., plants that are owned and operated by zombie firms) within a 50-mile radius of the observation location; (ii) *Under_Capitalized* captures the proportion of undercapitalized banks (equity-to-assets ratio < 4%) with operations (i.e., branches) within a 50-mile radius of the observation location, weighed by the deposit share of the banks in that area; and (iii) the interaction of *Zombie_Plant_Pct* and *Under_Capitalized*. We control for *GDP_PC* which is state-level gross domestic product per capita. Significance levels of 10, 5, and 1 percent are represented by *, **, and *** respectively.

1950-2015	All Taxa			Non-bird Taxa		
Dep Var=	(1)	(2)	(3)	(4)	(5)	(6)
	$A_{i,j,t}$	$R_{i,j,t}$	$J_{i,j,t}$	$A_{i,j,t}$	$R_{i,j,t}$	$J_{i,j,t}$
INTRA	-0.166	-0.069	0.016	-1.947***	-0.798*	-0.083**
	(-1.594)	(-1.407)	(1.123)	(-3.366)	(-1.990)	(-2.337)
INTRA x Year79_91	0.187	0.059	-0.003	1.884**	0.672*	0.109*
	(1.632)	(1.327)	(-0.242)	(2.429)	(1.775)	(1.825)
GDP_PC	-0.055	-0.259*	0.002	0.547	-0.373	0.131
	(-0.131)	(-1.866)	(0.045)	(0.656)	(-1.214)	(1.074)
TAXA Location FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
State Clustering	Y	Y	Y	Y	Y	Y
Observations	48,262	48,262	39,968	14,145	14,145	10,735
Adjusted R-squared	0.936	0.937	0.694	0.878	0.834	0.269

Table 5 Zombie firms and pollution

This table examines the link between firm zombie status and plant-level pollution. The dependent variables are (i) *Total Releases* which is the natural logarithm of total toxic releases (Column 1); (ii) *On Site Releases* which is the natural logarithm of on-site toxic releases (Column 2); and (iii) *Off Site Releases* which is the natural logarithm of off-site toxic releases (Column 3). The independent variable of interest is *Zombie Rank* which is a decile ranking capturing the degree of zombieness of a plant using the criteria set out in Albuquerque and Iyer (2024), Favara, Minoiu, and Perez (2021; 2024). We control for *Firm Size* which is the natural logarithm of total assets and *BM Ratio* which is the natural logarithm of the book to market ratio. Significance levels of 10, 5, and 1 percent are represented by *, **, and *** respectively.

	(1)	(2)	(3)
VARIABLES	Total Releases	On Site Releases	Off Site Releases
Zombie_Rank	0.125***	0.115***	0.091***
	(5.585)	(5.387)	(5.541)
Firm Size	0.813***	0.768***	0.513***
	(24.692)	(24.263)	(17.286)
BM Ratio	0.014	0.007	-0.016
	(0.372)	(0.188)	(-0.529)
IND FE (NAICS 2 digits)	Y	Y	Y
Year FE	Y	Y	Y
Firm Clustering	Y	Y	Y
Year Clustering	Y	Y	Y
Observations	76,176	76,176	76,176
Adjusted R-squared	0.240	0.231	0.184

Table 6 Zombie firms and green innovation

This table examines the link between zombie firms and green innovation for our sample covering 1990-2015. The dependent variables are (i) *TT_Num_Green_Patent (t, t+T)* which is the natural logarithm of the number of green patents awarded between time *t* and *t+T*; (ii) *TT_Cites_Green_Patent (t, t+T)* which is the natural logarithm of the number of green patent citations between time *t* and *t+T*; (iii) *Mean_Num_Green_Patent (t, t+T)* which is the natural logarithm of the mean of green patents awarded between time *t* and *t+T* ; (iv) *Mean_Cites_Green_Patent (t, t+T)* which is the natural logarithm of the mean of green patent citations between time *t* and *t+T*. The independent variables of interest is (i) *Zombie_Plant_Pct* which is the percentage of zombie plants (i.e., plants that are owned and operated by zombie firms) within a 50-mile radius of the observation location. We control for *GDP_PC* which is state-level gross domestic product per capita. Significance levels of 10, 5, and 1 percent are represented by *, **, and *** respectively.

Dep Var=	Ln(TT_Num_Green_Patent, t-4, t)	Ln(TT_Cites_Green_Patent, t-4, t)	Ln(TT_Num_Green_Patent, t+1, t+3)	Ln(TT_Cites_Green_Patent, t+1, t+3)
Zombie_Plant_Pct	-0.006***	-0.006***	-0.012***	-0.014***
	(-9.228)	(-8.655)	(-21.189)	(-26.082)
GDP_PC	0.22	0.631***	-1.136***	-0.345**
	-1.519	-4.169	(-6.974)	(-2.238)
Location FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location Clustering	Yes	Yes	Yes	Yes
Observations	55,100	55,100	55,100	55,100
Adjusted R-squared	0.951	0.948	0.947	0.944

Table 6 cont.

Dep Var=	Ln(Mean_Num_Green_Patent, t-4, t)	Ln(Mean_Cites_Green_Patent, t-4, t)	Ln(Mean_Num_Green_Patent, t+1, t+3)	Ln(Mean_Cites_Green_Patent, t+1, t+3)
Zombie_Plant_Pct	-0.012***	-0.010***	-0.012***	-0.014***
	(-8.972)	(-6.670)	(-10.902)	(-11.502)
GDP_PC	1.234*	4.248***	-4.138***	1.834***
	-1.877	-8.267	(-8.275)	-3.632
Location FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location Clustering	Yes	Yes	Yes	Yes
Observations	55,100	55,100	55,100	55,100
Adjusted R-squared	0.746	0.728	0.726	0.677

Table A1 Frequency of zombie firms overtime

This table reports the frequency and proportion of publicly listed firms that are classified as zombie (i.e., highly leveraged and unprofitable) firms overtime using the criteria set out in Albuquerque and Iyer (2024), Favara, Minoiu, and Perez (2021; 2024). More precisely, we require that zombie firms have leverage above the sample annual median, interest coverage ratio (ICR) below one, and negative real sales growth over the preceding three years.

Year	No. of Firms	No. of Zombie Firms	% of Zombie Firms
1964	283	2	0.00707
1965	375	4	0.01067
1966	806	12	0.01489
1967	910	10	0.01099
1968	1012	12	0.01186
1969	1103	19	0.01723
1970	1188	44	0.03704
1971	1265	63	0.0498
1972	1829	62	0.0339
1973	2142	42	0.01961
1974	2230	100	0.04484
1975	2261	140	0.06192
1976	2317	92	0.03971
1977	2380	73	0.03067
1978	2620	75	0.02863
1979	2959	122	0.04123
1980	3207	207	0.06455
1981	3633	270	0.07432
1982	3851	383	0.09945
1983	4418	397	0.08986
1984	4717	299	0.06339
1985	4917	311	0.06325
1986	5172	489	0.09455
1987	5401	419	0.07758
1988	5241	382	0.07289
1989	5060	334	0.06601
1990	5009	468	0.09343
1991	5114	567	0.11087
1992	5253	418	0.07957
1993	6300	417	0.06619
1994	6651	335	0.05037
1995	6807	290	0.0426
1996	7228	361	0.04994
1997	7193	367	0.05102
1998	6781	294	0.04336
1999	6532	306	0.04685
2000	6254	332	0.05309
2001	5567	331	0.05946
2002	5144	396	0.07698

2003	4859	297	0.06112
2004	4796	192	0.04003
2005	4726	164	0.0347
2006	4621	173	0.03744
2007	4515	214	0.0474
2008	4205	235	0.05589
2009	3964	239	0.06029
2010	3829	221	0.05772
2011	3715	152	0.04092
2012	3651	138	0.0378
2013	3719	191	0.05136
2014	3873	200	0.05164
2015	3841	206	0.05363
2016	3720	276	0.07419
2017	3687	243	0.06591
2018	3687	221	0.05994
2019	3666	229	0.06247
2020	3807	375	0.0985
2021	4187	564	0.1347

Table A2 Frequency of zombie firms across industries

This table reports the frequency and proportion of publicly listed firms that are classified as zombie (i.e., highly leveraged and unprofitable) firms across industries using the criteria set out in Albuquerque and Iyer (2024), Favara, Minoiu, and Perez (2021; 2024). More precisely, we require that zombie firms have leverage above the sample annual median, interest coverage ratio (ICR) below one, and negative real sales growth over the preceding three years.

NAICS2	Industry	% of Zombie Firms
11	Agriculture, Forestry, Fishing and Hunting	0.06574
21	Mining, Quarrying, and Oil and Gas Extraction	0.080661
22	Utilities	0.028943
23	Construction	0.093042
31	Manufacturing	0.051124
32	Manufacturing	0.055311
33	Manufacturing	0.05778
42	Wholesale Trade	0.052067
44	Retail Trade	0.057984
45	Retail Trade	0.05395
48	Transportation and Warehousing	0.060532
49	Transportation and Warehousing	0.021833
51	Information	0.06062
52	Finance and Insurance	0.017008
53	Real Estate and Rental and Leasing	0.071469
54	Professional, Scientific, and Technical Services	0.059756
56	Administrative and Support and Waste Management and Remediation Services	0.054251
61	Educational Services	0.051912
62	Health Care and Social Assistance	0.051606
71	Arts, Entertainment, and Recreation	0.070604
72	Accommodation and Food Services	0.080228
81	Other Services (except Public Administration)	0.059444
92	Public Administration *(not covered in economic census)*	0.084287

A3 Distribution of taxa, observation locations and years across state

This table presents the distribution of BioTime biodiversity data (taxa counts, observation location counts, and years covered) across states. The sample period is 1950-2015.

State	Obs.	No. of Taxa	No. of Locations	No of Years
ALABAMA	353	1	12	30
ALASKA	361	2	72	27
ARIZONA	115	2	5	34
ARKANSAS	467	1	16	30
CALIFORNIA	744	2	29	32
COLORADO	293	4	77	33
CONNECTICUT	149	1	5	30
DELAWARE	88	1	3	30
FLORIDA	374	2	16	30
GEORGIA	418	3	50	36
IDAHO	6304	2	2037	38
ILLINOIS	837	1	29	57
INDIANA	98	2	4	42
IOWA	202	1	7	30
KANSAS	841	5	29	64
KENTUCKY	295	1	10	30
LOUISIANA	30	1	1	30
MAINE	145	1	5	30
MARYLAND	736	1	25	30
MASSACHUSETTS	209	2	8	30
MICHIGAN	6075	3	263	36
MINNESOTA	363	4	14	43
MISSISSIPPI	29	1	1	29
MISSOURI	236	1	8	30
MONTANA	32187	1	10812	30
NEBRASKA	88	1	3	30
NEVADA	30	2	2	30
NEW HAMPSHIRE	378	2	14	47
NEW JERSEY	89	1	3	30
NEW MEXICO	5629	4	746	38
NEW YORK	695	2	25	35
NORTH CAROLINA	748	3	193	38
NORTH DAKOTA	1654	1	830	30
OHIO	148	1	5	30
OKLAHOMA	119	1	4	30
OREGON	1179	3	95	51
PENNSYLVANIA	630	2	22	30
SOUTH CAROLINA	30	1	1	30
SOUTH DAKOTA	253	2	54	35
TENNESSEE	616	1	21	30
TEXAS	335	2	12	31

VERMONT	11	1	1	11
VIRGINIA	295	1	10	30
WASHINGTON	727	2	128	47
WEST VIRGINIA	284	1	10	46
WISCONSIN	1232	4	42	39
WYOMING	112	1	18	30

A4 Distribution of taxa, observation locations and states across years

This table presents the distribution of BioTime biodiversity data (taxa counts, observation location counts, and states covered) across years. The sample period is 1950-2015.

YEAR	Obs	No. of Taxa	No. of Locations	Number of States
1950	22	2	22	5
1951	23	2	23	5
1952	20	2	20	5
1953	4	2	4	3
1954	4	2	4	3
1955	21	3	21	7
1956	13	3	13	6
1957	21	3	21	6
1958	4	3	4	3
1959	7	3	7	5
1960	13	3	13	5
1961	14	3	14	4
1962	7	4	7	6
1963	8	4	8	6
1964	6	4	6	5
1965	11	4	11	8
1966	6	4	6	5
1967	8	5	8	7
1968	19	3	19	5
1969	5	3	5	4
1970	8	2	8	5
1971	15	3	15	7
1972	20	3	20	7
1973	10	3	10	6
1974	4	2	4	4
1975	10	3	10	5
1976	33	4	33	8
1977	40	5	40	8
1978	442	5	442	44
1979	413	5	413	45
1980	433	5	433	45
1981	459	6	458	45
1982	469	7	468	46
1983	501	7	499	46
1984	492	7	490	46
1985	492	7	490	46
1986	500	7	498	46
1987	481	7	479	46
1988	500	7	498	46
1989	724	7	722	46
1990	727	7	725	46

1991	698	7	696	46
1992	1068	7	1066	46
1993	1839	7	1837	46
1994	7057	8	7055	46
1995	7347	8	7342	46
1996	6483	8	6479	46
1997	1527	8	1523	46
1998	4575	8	4571	46
1999	1242	8	1237	46
2000	4727	8	4721	46
2001	2183	8	2178	47
2002	5172	8	5168	47
2003	3323	8	3318	47
2004	6260	8	6255	47
2005	1367	8	1361	46
2006	2098	8	2093	47
2007	1125	8	1120	47
2008	391	8	386	14
2009	368	7	363	14
2010	328	7	324	12
2011	319	7	315	9
2012	323	7	320	9
2013	314	7	310	7
2014	29	5	27	4
2015	17	3	17	3