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Publicity Rights and Integrated IP Strategy

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WIPO

Elvis' Ghost or Digital Replica?
Publicity Rights and Integrated IP Strategy *

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Abstract

"Rights of publicity" provide a degree of control over one's name, image, and likeness (NILs), and can have significant commercial value, especially with the advent of artificial intelligence and digital replicas. Although publicity rights have recently received substantial media and legislative attention, they have so far escaped the attention of economists. This article remedies that with the first empirical examination of publicity rights, using asynchronous changes in U.S. state laws to explore potentially welfare-improving economic incentives and the interaction of NIL protections with other intellectual property rights, thus laying the foundation for a new line of economic inquiry.

Keywords: publicity right, likeness, copyright, trademark, empirical, difference-in-differences

JEL Codes: O34, O33, K42, L82, Z10

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It is no secret that many celebrities (both living and dead) bank on revenues generated from their name, image, and likeness ("NIL"). For example, the estate of Elvis Presley reportedly generates millions of dollars per year from sources not directly related to Elvis' music rights. This includes selling Elvis merchandise, producing Elvis-themed events, and licensing his likeness for various uses, such as film and television. Michael Jordan has reportedly earned $1.5 billion for associating his persona with Nike products. The estate of Tupac Shakur earns money from "live" (holographic) performances despite the rapper dying several decades ago. With the latest wave of digitization, new digital replica uses and other commercial opportunities to exploit NIL assets have greatly expanded (Acemoglu and Restrepo, 2018; Brynjolfsson et al., 2023; Peukert, 2019).[1] At the same time, however, these new avenues for exploitation also include unlawful uses such as deepfakes. Indeed, as Figure 1 illustrates,[2] perceived violations of publicity rights spurred by recent technological changes related to artificial intelligence (Lutes, 2025) have increased dramatically. In addition to the growing role of AI in NIL policy debates, the issue has been further thrust into the limelight by recent legal disputes, such as the class action case against the National Collegiate Athletic Association (NCAA), the settlement of which granted $2.8 billion in compensation for use of NIL rights to collegiate athletes for the first time in US history.[3]

"Rights of publicity" (also referred to as "publicity rights") serve as one of the primary legal mechanism for excluding the unauthorized use of one's NIL, and they have been extensively discussed among legal scholars and in cultural studies (Rothman, 2018; Nimmer, 1954; Madow, 1993; Tan, 2007). While these rights are not always based in purely economic terms (they are often justified by way of normative values of fairness), it is nonetheless useful to understand the extent to which they affect related commercial activity, and how they might interact with other intellectual property rights (IPRs). So far, these rights have received very little attention in the economic literature (Posner, 1977; Landes and Posner, 2003a; Dogan and Lemley, 2005; Lutes, 2025). This paper is an important step towards filling that gap, providing the first systematic empirical evidence to inform public policy debates and strategic IPR management around NIL assets in the digital age (Nagaraj, 2018; Reimers, 2019; Giorcelli and Moser, 2020; Fosfuri and Giarratana, 2008; Appelt, 2009; Danaher et al., 2013; Kaiser et al., 2023; Castaldi et al., 2020; Peukert and Windisch, 2023).

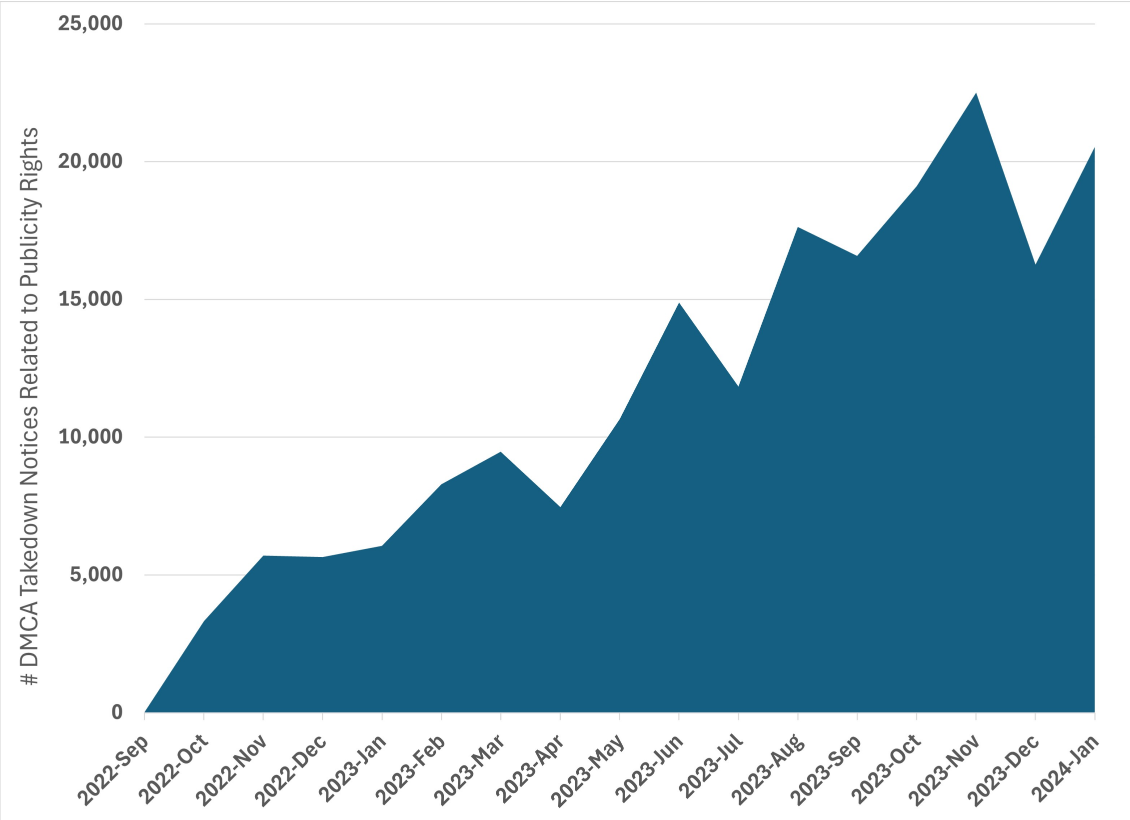
Noting that more research is needed to understand the full breadth of economic and management issues around publicity rights, here we narrowly focus on exploring the causal relationship

[1]For example, with new re-purposing technologies such as AI, celebrities are now more likely to survive the test of time and see new NIL uses, plausibly enabling the 'reanimation' and promotion of celebrities long after their death, or possibly the postmortem creation of new works.

[2]Figure 1 depicts NIL-related complaints submitted through the notice and takedown system first established through the Digital Millennium Copyright Act (DMCA). Importantly, the DMCA notice and takedown system was intended for copyright infringements, not infringements of other types of IP, such as publicity rights. Nonetheless, there is no mechanism preventing other types of complaints and we observe a non-trivial number of non-copyright complaints in the data. Excluding the initial substantial jump between September and October of 2022, we observe a 16% month-over-month growth rate between October 2022 and and January 2024 (equating to a roughly 195% annual growth rate), indicative of the growing perceived misuse of NILs online which coincides with the launch of large generative AI services in the last quarter of 2022.

[3]See, In re College Athlete NIL Litigation, No. 4:20-cv-03919, Dkt. 533 (N.D. Cal. Sept. 26, 2024).

Figure 1: Trends in Perceived Publicity Rights Violations Online



Notes: This chart tracks complaints about unauthorized use of an individual's persona overtime using DMCA takedown notices compiled by the Lumen project. We cannot systematically capture all such complaints; thus, we use keyword searches to identify complaints that specifically mention "deepfakes" as a proxy for such complaints. We observe no such complaints prior to September, 2022.

between losing publicity rights and subsequent changes in celebrity popularity, related commercial activities, copyright reliance, and trademark reliance. To do that, we exploit asynchronous changes in certain U.S. state laws regarding the application of postmortem publicity rights to celebrities residing in those states, combined with a battery of outcome variables from various official and online sources (including Google, YouTube, the Lumen project, the U.S. Patent and Trademark Office, and the U.S. Copyright Office).

At the outset, the theoretical relationship between publicity rights and the commercial activity related to NIL assets is not straightforward, nor is the role of publicity rights in an integrated IPR strategy. While exclusive rights may encourage celebrities to more actively promote and monetize their personas—potentially increasing their popularity and authorized commercial activities—restrictive enforcement could simultaneously suppress popularity and commercial opportunities flowing through (unauthorized) third-party channels. For a celebrity that intends to generate revenue solely through the exploitation of their persona, strong enforcement of publicity rights is clearly the strategic optimum. However, most celebrities have multiple interrelated revenue streams with cross-promotional effects between them, in which case these dual, countervailing effects create a strategic challenge to celebrity management and NIL asset owners, producing theoretical ambiguity as to the relationship between IPRs.

For example, copyrights and publicity rights can be complimentary insofar as a celebrity's persona can be used to promote the sale of copyrighted works, and copyrighted works can be used to bolster a celebrity's persona. Although copyrights and publicity rights clearly do not have the same scope of protection,[4] they can nevertheless serve as substitutes to the extent each offers a mechanisms for appropriating the value of the other under alternative business models.

To illustrate this, consider the case of Elvis Presley. Today, his estate generates revenue from both his music and his persona—revenue streams that evolve symbiotically. His distinctive persona enhances his music's popularity while his musical success elevates his persona's value, so that the combined value of the two when simultaneously exploited can be super-additive. The cross-promotional relationship between the two also offers a mechanism through which Elvis' estate can indirectly appropriate some of the value of one through exploitation of the other (Liebowitz (1985)), meaning that persona protections could serve as a partial indirect substitute for copyright protection and and copyright protection can similarly substitute for persona protections. Moreover, this interdependence creates strategic tensions as restrictive enforcement of publicity rights protecting the persona may inadvertently diminish music sales, and vice versa. Consequently, Elvis' estate must consider a spectrum of IPR strategies, from predominantly monetizing his persona while liberally distributing creative works at one end, to predominantly monetizing his music while permitting broader persona usage, at the other end. Arguably, the optimal, profit-maximizing protection strategy and intertemporal business model choice depends on several factors: the relative elasticity of different revenue sources, the cross-promotional effects between creative works and persona consumption, and critically, the availability, cost and enforceability of various types of IPRs. The conceptual framework developed in this paper primarily focuses on the latter putting forward three main research questions: (1) whether NIL protections effectively increase celebrity popularity and commercial exploitation, (2) whether publicity rights and copyrights function as complements or substitutes, and (3) how the availability of such rights changes reliance on trademark protection, given their overlapping yet distinct characteristics.

Our empirical findings indicate that losing publicity rights causes reduced popularity and is associated with greater competition around NILs, indirectly implicating effects on related commercial activity. This is in line with prior IPR research that documents generic entry and increases in competition as rights expire (Reimers, 2019; Morton, 2000). We also find a strong substitutional relationship between publicity rights and copyright reliance, suggesting strategic shifting between the two types of IPRs. Similarly, with respect to trademarks and publicity rights, we find that the dominant relationship is substitutional, consistent with prior work on IPR bundling and the strategic use of trademark protection (Kaiser et al., 2023; Castaldi, 2023). In general, our findings indicate that publicity rights, where available, can be welfare improving by shifting the supply

[4] Copyright protects creative or expressive works affixed in a tangible medium, whereas publicity rights protect less tangible aspects of the public persona. It is technically possible for these rights to overlap; however, this is relatively rare.

curve for persona-related goods and services to the right. However, the impact of changing policies around publicity rights may be dampened by rightsholders' compensating behavior in terms of their broader IPR strategy and business model choices.

In the remainder of this article we first provide further background on publicity rights and discuss related literature in Sections I and II, respectively, then turn to our data and empirical strategy in Section III. Our empirical results are reported in Section IV, with robustness and empirical concerns discussed in Section V, followed by a discussion of the results and their policy and managerial implications in Section VI. Section VII concludes. Additional robustness tests and alternative specifications are available in the supplemental Appendix.

I Background and Conceptual Framework

For some celebrities, such as social media "influencers", NIL exploitation may be their primary or even sole source of income. Others, such as popular musicians or actors, whose creative practices more heavily rely on NIL aspects, may use them to directly generate supplemental income (e.g., through merchandise sales or endorsements) or as a mechanism to bolster their primary income source (e.g., through promoting their music). In theory, this sort of exploitation can have positive social value and substantial strategic value for firms. For example, the endorsement of a discerning, reputation-conscious celebrity can act as a credible signal of value, thus reducing consumer risk and search costs in purchasing decisions, mitigating quality uncertainty in creative and other markets (Caves, 2000). Separately, the supplemental income a recording artist earns from selling merchandise could plausibly reduce the cost of accessing that artist's music, thus allowing for broader consumption.[5]

Nevertheless, the ability of individuals to commercially exploit their NILs in these ways depends on, among other things, whether individual can exclude others from using them. This is because overuse or misuse of one's NIL can, in principle, diminish their residual value. If a celebrity cannot exclude sellers from associating his or her persona with their product, that celebrity's endorsement will no longer hold signal value. If a musician or actor cannot restrict others from selling merchandise based on his or her persona, then competition would drive related profits to zero.

Publicity rights are intended to confer certain exclusive rights related to a celebrity's NIL. By way of background, these rights originate from personality rights that grant control over the recognizable aspects of celebrities' identity, shielding celebrities from defamation and unauthorized commercial uses of their NIL (Rothman, 2018). However, over time, they have developed into

[5]For a rational producer of creative works to produce those works, they must be able to earn revenues at least equal to their production costs. Their primary source of revenue typically comes from selling copies of their works, streaming, or by playing concerts, and producers must set the access price high enough to recoup their costs. However, if they can offset some of their costs through other means (e.g., merchandise sales), then they need not charge as much for access in order to fully recoup their production costs. This essentially reduces a producer's reservation price enabling them to produce works that may not have otherwise been commercially viable.

full-fledged commercial rights in some jurisdictions, similar to copyright and other types of IPRs, granting rightsholders temporary exclusivity over market exploitation (Nimmer, 1954; Klein and Cohn, 2022). This includes the possibility to transfer, license, or defend publicity rights, for purposes of commercially exploiting celebrity's NIL, either by the celebrity, their estate, or some other authorized party. Anecdotal evidence suggests that publicity rights, to include postmortem rights, can have a high market value, particularly in the case of superstars.[6]

Legal protections related to rights of publicity are not harmonized on a federal level in the U.S. (although, at the time of writing there are legislative efforts to establish federal protection);[7] instead, they are exclusively rooted in state laws. More than half of all U.S. states grant lifetime publicity rights; however, currently only 20 states grant protection after death, and until recently, that number was as low as 15.

Two factors of the modern publicity rights landscape are instrumental to much of our research design. The first is that, as previously discussed, publicity rights are determined at the state level, meaning there are multiple publicity rights regimes within the U.S., each pertaining to a distinct population. The second important factor is the set of asynchronous changes in state laws that occurred in recent years. In particular, five US states changed their laws to offer postmortem publicity rights where none existed prior to the relevant statutory change. These statutory changes happened at different points in time and each provides a clear cutoff such that people dying before have no postmortem rights, and people dying after have full postmortem publicity rights. The five states are, New York (statutory change effective in 2021), Alabama (statutory change effective in 2015), Arkansas (statutory change effective in 2016), Hawaii (statutory change effective in 2009,), and Virginia (statutory change effective in 2015).[8]

From a conceptual standpoint, the connection between publicity rights on the one hand, and celebrity popularity and the commercial activity related to NILs on the other hand is multifaceted. In principle, having protection of NILs may encourage celebrities to promote and monetize their persona to a greater extent, thus leading to greater popularity and increased commercial activities through channels controlled or authorized by those celebrities. At the same time, using publicity rights to restrict use of NILs by third parties may decrease the popularity and commercial activities that would otherwise flow through those alternative channels. Which of the two effects will dominate is the first empirical question we seek to answer with our data.

[6]The Michael Jackson estate case is a prominent example where U.S. tax authorities initially estimated his publicity rights to be worth more than 3 million USD (Klein and Cohn, 2022). The arguments presented in the Jackson case also suggest that the economic value of such rights can be a matter of substantial disagreement: alternative estimates from parties in court ranged from as low as $2,000 to more than $430 million. More recently, with new tech opportunities for the commercialization of celebrities after their death, living superstars like Justin Bieber, the Red Hot Chilli Peppers, and Bob Dylan have been able to sell rights to their content to large investors outside the creative industries. Some of these multi-million deals have also included the transfer of publicity rights, again indicative of their market value.

[7]"The Nurture Originals, Foster Art, and Keep Entertainment Safe (NO FAKES) Act of 2024 is a bipartisan bill that would protect the voice and visual likeness of all individuals from unauthorized computer-generated recreations from generative artificial intelligence (AI) and other technologies."

[8]South Dakota also saw a statutory change with respect to publicity rights; however, there are so few celebrities to whom South Dakota publicity rights apply that we do not include it in our analyses.

The connection between publicity rights, copyrights, and trademarks is, perhaps, somewhat more complex, given they offer protections for ostensibly different things. It is thus useful to contextualize these connections. To that end, we return to the illustrative (and semi-hypothetical) example of Elvis Presley. Elvis' estate generates revenue from his music and from his persona (e.g., through merchandise or the use of his image in movies). In a sense, these are separate revenue streams, but they are nonetheless inextricably intertwined. Elvis' music would likely not have reached the level of popularity that it did, had it not been for his conspicuous public persona and diligent brand management. In the same vein, his public persona likely would not have had developed the same value, had it not been for the desirability and omnipresence of his music. The two evolved together. Both during his life and now through his estate, the use of Elvis' persona promotes music sales on the one hand, and exposure to his music increases the demand for his persona on the other hand (Bertrand, 2000).

Thus, while Elvis' estate enforcing stringent restrictions on the unauthorized use of his persona may increase his estate's persona-related revenue streams, it may also have negative effects on the sale of his music. Similarly, stringent restrictions on the unauthorized distribution of his music may increase those revenue streams, but it may also have negative effects on the value of his persona. So, how might Elvis' estate incorporate these cross-promotional effects into its IPR enforcement strategy?

To answer that, consider the spectrum of business models available to Elvis' estate. At one extreme, the estate could put no restrictions on the use of Elvis' persona, instead capturing value exclusively through music sales, recognizing that broader use of his persona (even by unauthorized third parties) leads to more music sales. At the other end of the spectrum one can image a business model where the music is given away for free and the estate captures value exclusively through exploitation of his persona, again recognizing that broader consumption of Elvis' music leads to increased sales related to his persona (the more fans of his music there are, the greater the demand for merchandise and other representations of his persona will be). These IPR strategies are clearly very different from one another, but they both, nevertheless, represent ways of appropriating overlapping pools of value.

In reality, the estate's business model falls somewhere between those two extremes. Exactly where the optimal point falls along the spectrum depends on the relative elasticity of the various revenue sources and the relative marginal promotion value derived from consumption of Elvis' persona versus consumption of his music. But it also critically depends on what protections are available to the estate, the cost of maintaining those protections, and its capacity for enforcing various IPRs. If the estate cannot restrict the exploitation of Elvis' persona (e.g., due to a lack of relevant IPRs), then they would rationally gravitate towards the copyright-centric end of the spectrum, with stronger enforcement of music copyrights and less attempted enforcement related to his persona. Alternatively, if strong IPRs related to NILs are available, the estate might want to move closer to the persona-centric end of the spectrum, in which case it might strategically engage in less enforcement of his music rights, and more enforcement of NIL rights.

The idea that there may be cross-promotional effects between the consumption of a celebrities creative works and the consumption of their persona suggests that the two types of IPRs may be complimentary. However, to the extent that the two types of IPRs can essentially appropriate the same pool of underlying value, they may also substitute for one another through shifts in IPR strategy. Whether the complimentary relationship or substitutional relationship dominates is the second empirical question we seek to answer with our data.

Further complicating decisions around IPR strategy, if Elvis' estate elects to adopt a persona-centric business model, it must consider how to enforce rights around NILs. So far we have primarily discussed publicity rights as NIL protection, but trademarks also provide ways to protect one's NIL. Although there are meaningful limits on exactly what can be trademarked with relation to one's persona, there is substantial overlap between NIL-related trademark protection and publicity rights. Moreover, even if trademarks offer a more limited scope of protection, they have the advantage of nationally harmonized regulation and arguably less legal ambiguity, relative to publicity rights (which rely on a patchwork of inconsistent state laws). Moreover, trademarks do not have term limits, as they can be renewed indefinitely, whereas many publicity rights regimes limit those rights to a given number of years after the death of the celebrity. Thus, electing to register NIL-related trademarks instead of, or in addition to, relying on publicity rights may be a sensible choice for some.

Indeed, Elvis' estate does, in fact, own registered trademarks related to his persona.[9] His persona may also be protected by Tennessee's postmortem publicity rights.[10] However, there appears to be enough ambiguity around Tennessee's postmortem publicity rights that the extent to which Elvis's persona is protected is unclear.[11] Thus, Elvis' use of trademarks may be a substitution for (uncertain) publicity rights. But it may also be a calculated, strategic redundancy meant to further strengthen the estate's legal position with respect to Elvis' NIL. Were his publicity rights strengthened or made less ambiguous, we may plausibly see less reliance on trademark protection. It is also possible that we could see the opposite result - increased publicity rights leading to more trademark reliance. For example, if publicity rights are available, Elvis' estate may be more inclined to shift away from a copyright-centered business model towards a persona-centered business model. That may warrant greater investment in protecting Elvis' persona through trademark in addition to publicity rights. Which of these two possibilities is the dominant relationship is the third empirical question we seek to answer.

[9] Elvis Presley, as a name, is registered as a trademark and used on many goods and services. The oldest trademark was filed in 1956 for printed matter, photos, albums, postcards, paper doll books, coloring books, and coin books. See e.g., https://vernalaw.com/elvis-presley-what-ip-rights-are-there-in-the-king/.

[10] Postmortem rights are often contingent on where a celebrity resided at the time of their death; Elvis resided in Tennessee when he died.

[11] See, https://rightofpublicityroadmap.com/state_page/tennessee/.

II Related literature

Scholars tend to disagree on the potential economic effects publicity rights, should any exist. In principle, publicity rights can help celebrities build their brand, to which, aspects of their identity are integral. In this way, such rights might provide economic incentives for rightsholders to invest in marketing, promotion of content, merchandise, and brand endorsements as well (Dogan and Lemley, 2005). In contrast, other scholars have argued that granting publicity rights can effectively limit commercialization and over-exploitation of the persona. As stated in Landes and Posner (2003a), "the rationale for providing strong publicity rights is not to encourage greater investment in becoming a celebrity (the incremental encouragement would doubtless be minimal), but to prevent the premature exhaustion of the commercial value of the celebrity's name or likeness." In that way, publicity rights could be viewed as a facilitator of continued creative activities insofar as they can provide greater financial means for creators to continue producing creative works.

Although little economic research (and no empirical research) with respect to publicity rights exists, this article complements several other distinct bodies of literature. First, and most generally, our work contributes to the economic literature on IPRs as a means of formal protection of intangible assets, in particular in creative sectors. Previous studies have focused on the strategic use and welfare effects from either copyright (Nagaraj, 2018; Reimers, 2019; Giorcelli and Moser, 2020; Cuntz, 2022; Cuntz and Sahli, 2023; Cuntz et al., 2023) or trademark protection (Fosfuri and Giarratana, 2008; Appelt, 2009; Kaiser et al., 2023; WIPO, 2013; Castaldi et al., 2020) on markets. Existing work shows how IPRs can provide important incentives to invest in and create new works while, at the same time, reducing access to existing works. Our research expands this line of thinking to now include publicity rights in the canon of rights providing market incentives. Again, we are first to empirically test their ability to facilitate the promotion and commercialization of celebrities and their relationship with copyright and trademark protections.

Second, our work also closely relates to the growing body of literature on IPR bundling, wherein firms package multiple forms of intellectual property (e.g., patents, copyrights, trademarks, and trade secrets). A key debate in this literature is whether different IPRs serve as substitutes or complements in firm strategy, innovation incentives, and market competition. Theoretical models provide competing views: Anton and Yao (2004) argue that firms may opt for trade secrecy over patents when public disclosure could erode competitive advantages, suggesting substitutability, while Gallini and Scotchmer (2002) analyze how firms may favor copyrights over patents in software given differences in enforcement costs. Boudreau et al. (2022) demonstrate that mobile app companies select between patent and copyright protection based on differentiation strategy—novel design favors patents while content exclusivity favors copyrights. Conversely, Shapiro (2001) contends that firms strategically bundle patents to create patent thickets, indicating complementarity, while Lemley (2000) argues that firms integrate trademarks and copyrights to strengthen brand identity.

Empirical studies confirm that IPR bundling varies across industries and contexts. In pharmaceuticals and biotechnology, IPRs function as complements, with firms employing patents alongside trade secrets for complex innovations (Cockburn and Henderson, 2003) and bundling patents with regulatory exclusivities (Hall et al., 2014). By contrast, in software and IT, IPRs often serve as substitutes—Bessen and Hunt (2007) find software firms rely on copyrights over patents due to lower enforcement costs, while Graham and Mowery (2006) show open-source firms avoid patents for alternative licensing models. In creative industries, Landes and Posner (2003b) highlight complementarity between copyrights and trademarks in enhancing brand value, while Gans et al. (2019) demonstrate that digital platforms bundle multiple IPRs to combat piracy. Work by Llerena and Millot (2013) confirms that trademark-patent relationships are complementary in pharmaceuticals but substitutive in high-tech sectors, while Garanasvili et al. (2018) find large firms in copyright-intensive industries more likely to bundle multiple IPRs.

The bundling of IPRs has broad implications for policy and firm strategy. From a regulatory perspective, excessive IPR bundling may extend market power (Hemphill and Sampat, 2012), though firms leveraging complementary IPRs can enhance innovation incentives and reduce investment uncertainty. Harabi (1994) reveals that firms' preferences for patents or trade secrets depend on industry-specific factors. These findings underscore the importance of industry context in shaping optimal IPR strategies and highlight the need for further research on digital transformation and evolving enforcement mechanisms. Our work extends this body of research to now include publicity rights.

We also contribute to the economics of digitization (Acemoglu and Restrepo, 2018; Brynjolfsson et al., 2023; Yilmaz et al., 2023) and, in particular the emerging literature on the law and economics of artificial intelligence (Kretschmer et al., 2023; Handke et al., 2021; Peukert, 2019; Peukert and Windisch, 2023; Lutes, 2025), given that emerging AI technology is the impetuous for renewed legislative interest in publicity rights. The latter area centers on the role and design of legal frameworks in new tech developments and the economic implications of legal reform. Our research suggests that, beyond the more standard types of IPRs, such as copyright, trademarks, or patents, currently discussed in the context of artificial intelligence regulation, other parts of the legal framework such as publicity rights warrant consideration. This is also because there might be 'synergies' between different type of rights (Klein and Cohn, 2022).

In a less direct way, our research also adds to the long-standing discussion on superstar economics and their prominent position in creative sectors (Rosen, 1981; Adler, 1985). With our focus on celebrities, this research can provide an alternative or complementary explanation for high levels of market concentration, superstar dominance and their general ability to command higher profits. Separately, we also add to the line of marketing research looking at celebrity-endorsed marketing (Schimmelpfennig and Hunt, 2020; Bennett et al., 2021). Among other things, existing research suggests that up to 25 percent of all U.S. advertising is celebrity-based and that this is a more lucrative segment of the market compared to other countries (Schimmelpfennig, 2018). Again, the existence of publicity rights may be one plausible and potentially important reason why such a market has successfully developed.

III Empirical Framework

Our general strategy exploits the fact that, upon death, some celebrities are able to retain publicity rights while other similarly situated celebrities lose their publicity rights, depending on the state and year in which a celebrity died (relative to the timing of certain state-level statutory changes). Within the time period we examine, some states have continuously offered postmortem publicity rights, some states have never offered postmortem publicity rights, and other states experienced statutory changes that allowed publicity rights for celebrities who died after some cutoff date and no rights for those who died before the cutoff. Our empirical strategy mainly focuses on the latter group, using the asynchronous change in state statutes as a source of exogenous variation.

We use celebrities who lose publicity rights at the point of their death as a treatment group and those who retain publicity rights after death as a control, employing a difference-in-differences design with both time- and state-level fixed effects to account for unobservable factors.[12] The plausibly exogenous statutory changes account for potentially endogenous sorting of celebrities between states with and without postmortem publicity rights.[13] This framework is intended to isolate the causal relationship between the loss of publicity rights and certain outcome variables. These outcome variables (discussed further below) are measures of a celebrity's popularity, the commercial value of their NILs, their reliance on copyright protection, and their reliance on trademark protection.

In the remainder of this section we present our primary data, variables, and general empirical strategy (with additional details in subsequent sections).

A Data and Variables

Our main data source is a sample of celebrities and people of public interest domiciled in the United States when dying. It is drawn from the Wiki-based 'notable people' database (Laouenan et al., 2022).[14] Importantly, this data provides information on when each individual died and their

[12]We note that typically a treatment group is the group to which a policy change applies. However, in this case, while the policy change distinguishes the control and treatment groups, the policy change is not, itself, the treatment. Rather, treatment occurs at death for those in the treatment group. All celebrities in both the treatment and control groups have publicity rights prior to death, and the relevant change is the loss of those rights for a subset of celebrities (those who died prior to the policy change and are thus in our treatment group).

[13]Because sorting between states is unlikely to happen instantaneously, this approach likely does a reasonable job of controlling for shorter-term endogeneity. However, over a longer timeframe, choices of where one lives become more fluid. To the extent this sort of longer-term endogenous sorting occurs, our results may be bias towards zero, thus underestimating the true long-term treatment effect.

[14]The database cross-verifies bibliographic information, including date and location of birth and death, via various editions of Wikipedia and Wikidata and contains 2.29 million individuals living between 3500 BC and 2021 AD (Laouenan et al., 2022).

state of residence at the time of death. This tells us the publicity rights regime (or lack there of) that is applicable to any given individual in our sample.[15]

We are interested in measuring the effects of losing publicity rights on the popularity and commercial value of celebrity NILs and on the reliance of celebrities on copyright or trademark protection as a substitute for or complement to publicity rights. We use data from Google Trends, Google's Keyword Planner (KWP), the U.S. Copyright Office, U.S. Patent and Trademark Office, and the Lumen project to proxy for these things.[16] A summary of the data sample is provided in Table 1.

Using the Google Trends tool through an API we collect granular information on the volume of U.S. based Google searches related to each celebrity in our main sample. Monthly search information from the service is available from 2004 up to the present day.[17] Specifically, our data provides a relative measure of the frequency with which Google users searched for a particular celebrity's name. This provides a direct measure of a celebrity's online popularity, which itself serves as a proxy for overall popularity and an indirect indicator of commercial activity (since popularity is likely a significant contributor to commercial activity in many cases).

For a more direct measure of commercial value we use several other outcome variables, the data for which comes from Google's Keyword Planner (KWP) - a tool within the Google Ads platform. KWP reports advertisers' bids for keywords (measured as "cost-per-click") and the level of competition for a keyword. When a website owner wins a bid for a search term, their website is listed at the top of the search results returned by Google, potentially driving more traffic to that website than would occur with purely organic search results. The market price for a search term logically reflects more than just the popularity of that search term; it also reflects the extent to which users performing the searches can be converted to revenue. In that way, KWP data more directly and more broadly captures the potential commercial activity related to a celebrity. However, one meaningful limitation of this data is that it is only available for the most recent 12 months, which restricts the empirical designs that can be applied to the data.

The next relationship we examine is that between publicity rights reliance and copyright reliance for those celebrities who can rely on both (e.g., a recording artist who relies on both their persona

[15] We limit the sample to well-known individuals in 'core culture' (e.g., writers, painters, singers, musicians, etc.) and 'periphery' occupations (e.g., journalists, architects, models, designers, presenters, etc.). These notable creators account for roughly 1/3 of all individuals recorded in the data. We further restrict the sample to celebrities dying after 2003 (data for many of our outcome variables are not available prior to 2004).

[16] We also collect and analyze data from YouTube and Google Shopping; the effects on these outcome variables (discussed in the Appendix) are largely inconclusive. Separately, we collected data from Google's N-Gram Viewer, which provides annual counts of each time a particular celebrity name appears in a book. However, this data proved uninformative since it is currently only updated through 2019, thus missing several key policy changes regarding publicity rights.

[17] One significant limitation to this data is that the tool only provides relative measures of search volume and not absolute measures. Moreover, the measures are constructed to be relative with respect to time and with respect to the limited number of search terms that can be inputted at one time. For that reason, the the Google Trends output for any given search term entered will change depending on the time frame requested and the other search terms to which the user chooses to compare it. Despite these challenges, the measure of web traffic via Google has become a commonly used measure and has recently been adopted in several research articles in areas such as finance and forecasting (Huang et al., 2020; Jun et al., 2018), health care (Nuti et al., 2014), popularity (Malagón-Selma et al., 2023), or movie piracy (Cuntz and Bergquist, 2022).

and music to generate revenue). We seek to understand the extent to which the relationship is complementary or substitutional (or, alternatively, if the two are independent of one another). To do this, we use two separate outcome variables. The first is the count of copyright registrations submitted by a celebrity or their estate, which we extract from the U.S. copyright registrations dataset (Lutes et al., 2025). While this serves as logical proxy for copyright reliance, it is likely a relatively rough measure.[18] Thus, we incorporate a second measure of copyright reliance - one that directly measures levels of enforcement activity: take-down notices submitted to online content platforms (e.g., YouTube) by rightsholders under the authority of the Digital Millennium Copyright Act (DMCA). The notices instruct the recipient to remove content that the submitter claims infringes upon their copyrights. We compile data on millions of online take-down notices using API access to the Lumen database (Lumen, 2024).

The final relationship we examine is that between publicity rights and trademark protection. For this we use data from the US Patent and Trademark Office on trademark assignments (United States Patent and Trademark Office, 2024). We match trademark registrations and renewals based on exact celebrity names.[19] The trademark data provides us with the names of rightsholders, the date a trademark was registered, the trademark text, when and if it was renewed, and when and if it was relinquished.

B Descriptives

Before turning to our empirical strategy, we first provide observations about basic patterns in our outcome variables with respect to the availability or lack of publicity rights, and discuss potential sources of bias. First, Table 1 provides summary statistics for all outcome variables. Next, Table 2 provides raw relationships between the lack of publicity rights and measures of our outcome variables by simply regressing the latter on an indicator for the former. Additionally, we plot the raw data and trend lines for our primary outcome variable (Google search volume) in Figure 2 (all data) and Figure 3 (by state). We also show average Google search volume by year in Figure 4.

Because there are clear differences between states and systematic changes over time, the raw relationships reported in Table 2 likely suffer from unobserved variable bias. For example, the way

[18] Registering one's copyright is not a requirement in the U.S. (copyright is automatic once a qualifying creative work is affixed in a tangible medium), but it is substantially more difficult to enforce unregistered copyrights, and the remedies available to rightsholders upon successful enforcement are substantially diminished without registration (Lutes et al., 2025). Thus, it stands to reason that rightsholders who intend to rely on and commercially exploit their copyrights have a high propensity to register their copyrights. Nonetheless, there is a singular fixed (and relatively low) cost associated with registering one's copyright; thus, for a particular work, copyright registration provides only a threshold indicator of a rightsholder's intent to rely on and enforce their copyrights. So long as the value of copyright reliance and enforcement exceeds the cost of registering ($65 at the time of writing), the rightsholder will register, and otherwise not. The number of copyrights a rightsholder chooses to register can be indicative of the intensity of their reliance on copyright, but it is likely a noisy measure, as the number also depends heavily on the productivity of the creator and the medium in which they operate. For example, a film maker may have far fewer copyrights than a songwriter simply because the unit of production differs between the two mediums (a feature film is a much larger production than is writing a song, yet both would directly result in a single copyright).

[19] This means that other branded products and services not directly associated with the celebrity name are not considered. More concretely, in the case of Elvis Presley, this means that while his trademark "Elvis Presley" (registration no. 97184454) would be matched by our algorithm, other trademarks registered by his estate such as "Graceland" (no. 73478484) or the "Viva Las Vegas" (no. 77027387) would not be detected and are hence not considered in the below analysis.

Table 1: Summary Statistics

Outcome Variable	**Data Type**	**Obs.**	**Celebs. Trt. Gr.**	**Celebs. Ctrl. Gr.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Google Search	Pan.('04-'23)	26,360	1,099	219	9.11	11.59	0	100
Google KWP								
Cost per Click	Cross Sect.	147,027	100,934	46,093	0.06	1.11	0	366
Comp. Index	Cross Sect.	147,027	100,934	46,093	0.01	0.06	0	100
Copyright Regs.	Pan.('04-'20)	13,651	685	118	0.15	0.82	0	24
DMCA Takedowns	Pan.('04-'23)	15,480	659	115	0.04	0.31	0	7
Trademarks								
Ever Registered	Cross Sect.	123,392	38,674	84,718	0.03	0.17	0	1
Has Active	Pan.('04-'23)	316,080	176	13,823	0.01	0.09	0	1

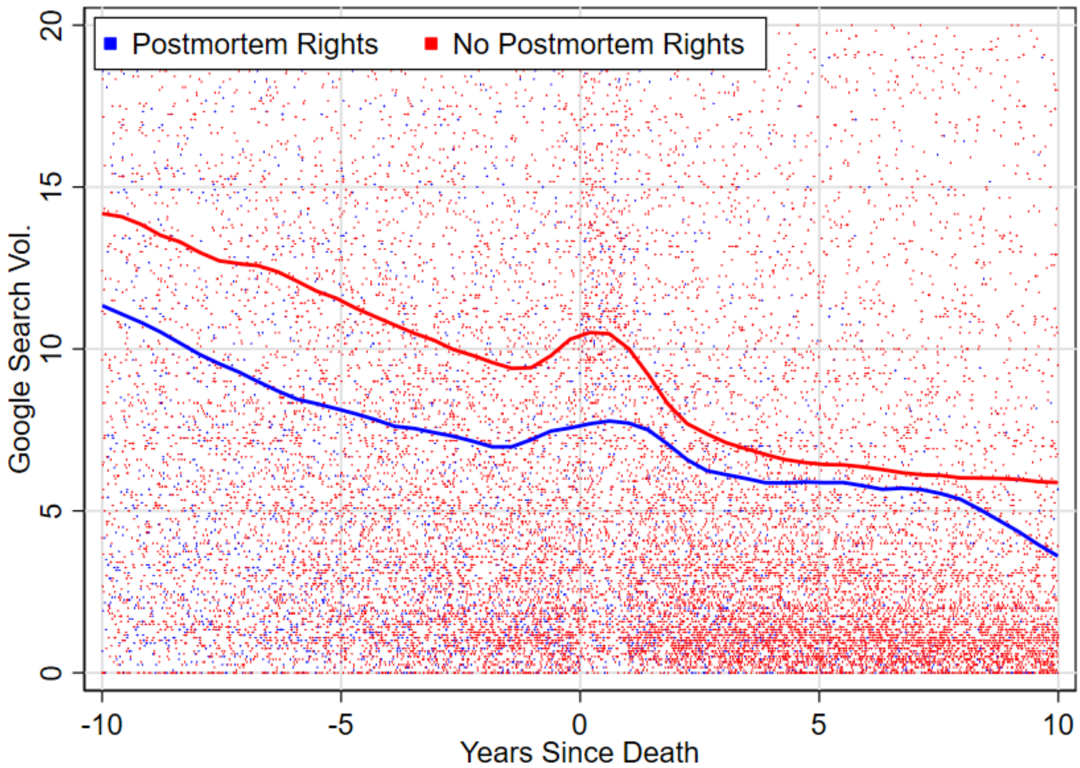
Notes: "Data Type" indicates whether the data is a panel or cross sectional, and the date range of the former. Panel periods are one year. "Celebs. Trt. Gr." and "Celebs. Ctrl. Gr." report the number of unique individuals represented in the treatment and control groups respectively. For panel data sets, the treatment group is comprised of celebrities who eventually lost publicity rights (at death) and the control group is comprised of celebrities who retained publicity rights after death. For cross sectional data, the treatment group is comprised of celebrities who never had publicity rights and the control group is comprised of celebrities who had publicity rights during their life. Google search search volumes are measured on an index from 0 to 100. "Cost per Click" is measured in dollars. Copyright registrations and DMCA takedown notices are counts per year, per celebrity. All trademark variables are binary.

Table 2: Raw Relationships Between Outcome Variables and Publicity Rights

	(1) Google Search Vol.	(2) Copyright Registrations	(3) Copyright Enforcement	(4) Trademark Registration
No Postmortem	-3.238	-0.005	0.185	-0.002
Rights	(0.303)	(0.016)	(0.029)	(0.002)
Constant	10.164	0.163	0.355	0.033
	(0.279)	(0.015)	(0.089)	(0.001)
R^2/Psuedo	0.022	0.000	0.000	0.000
Root MSE	10.85	0.85	10.54	0.18
Obs.	25,042	12,848	14,706	123,458

Notes: Estimated using OLS. Standard errors (in parentheses) are clustered at the state level.

Figure 2: Google Search Volume - Raw Data



Notes: Point in this chart represents Google search volume by celebrities with and without postmortem rights over time (relative to the year of death). Lines represent kernel-smoothed average Google search volume. Vertical axis is truncated at 20 for clarity - the actual range of values is 0-100.

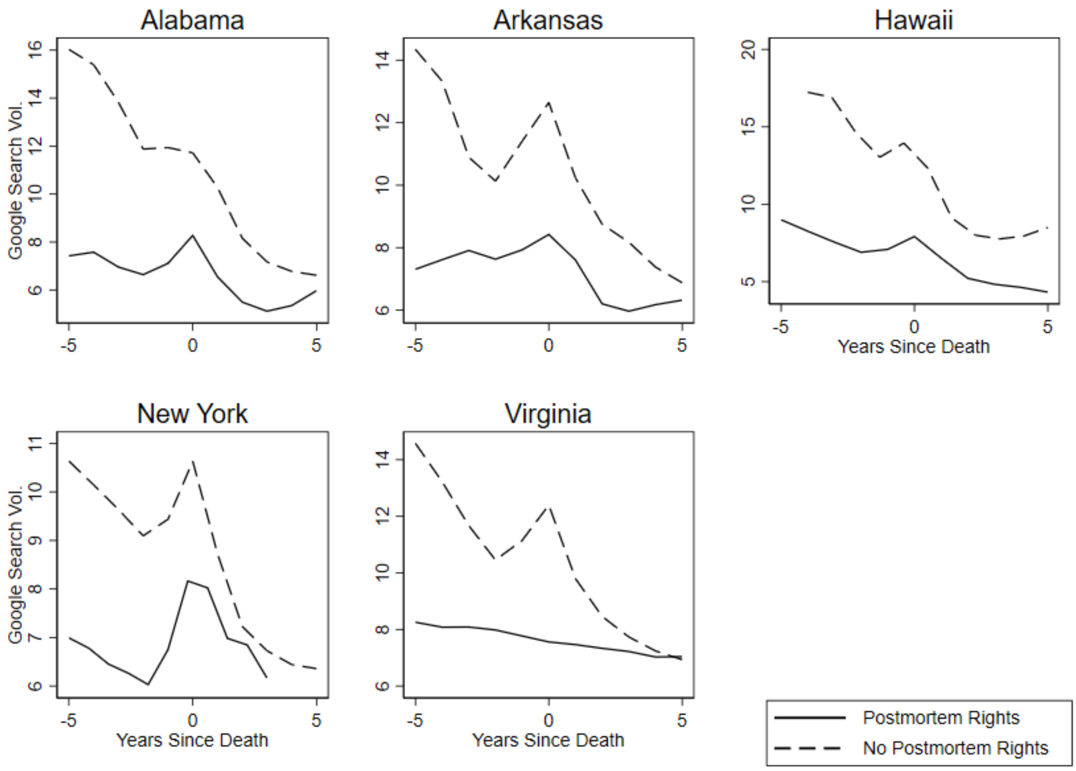
that Google measures search volume combined with user behavioral changes over time means that average relative search volume, using Google's measurement methodology, decreases over time, as can be seen in Figure 4.[20] Thus, celebrities who were alive and popular in earlier time periods tend to have a higher relative search volume than those who were alive and popular in later time periods as an artifact of Google's measurement methodology, separate and aside from any real differences. This is problematic because those who died in earlier time periods are more likely to lose publicity rights than those who died in later time periods, producing a potentially spurious correlation between having postmortem publicity rights and lower Google search volume measures, potentially biasing our estimates.

Similar concerns exist when comparing celebrities in different states. A state like Hawaii may have systematically more popular celebrities than a state like New York.[21] Because Hawaii started offering postmortem publicity rights 12 years before New York did, the subset of celebrities with

[20]Google measures the number of searches for a particular search term as a proportion of all Google searches (for any search term) in the same time period. It then normalizes the results so that the time period with the largest relative volume of searches equals 100. Thus, the value for any particular year is determined by, 1) the actual number of searches for that search term in a given period, 2) the total number of Google searches performed by all users in the same time period, 3) and the proportional difference in search activity between that time period and the time period with the maximum number of searches. The second element (the denominator) is clearly not time consistent and likely increases over time as the use of Google's search engine broadens and expands. For that reason, a given number of searches in an early time period may produce a higher relative value than the same number of searches in a later time period.

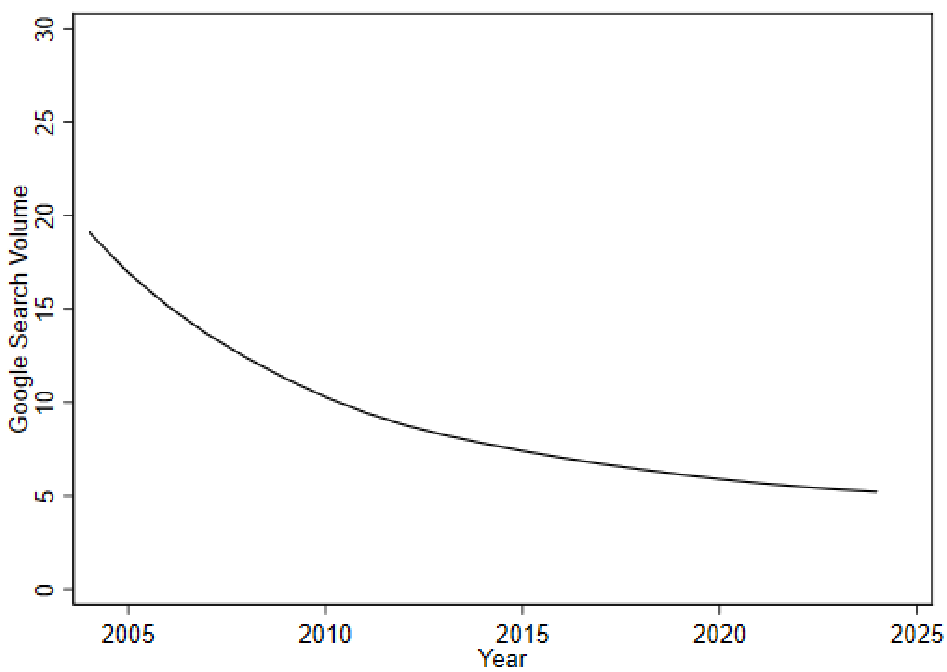
[21]This is because New York, in addition to being the home of ultra-famous celebrities, has a long tail of minor celebrities, decreasing average popularity.

Figure 3: Google Search Volume by State - Raw Data



Notes: Charts plot kernel-smoothed average Google search volume for those with and without postmortem rights.

Figure 4: Mean Google Search Volume by Year



Notes: Charts plot kernel-smoothed Google search volume by year, averaged across all celebrities in the sample.

postmortem rights is unevenly weighted towards the more popular Hawaiian celebrities, again, potentially biasing our raw estimates. Our empirical design (discussed below) is intended to address these potential issues. Additional empirical concerns are discussed in Section V.

C Empirical strategy

We now turn to formalizing our empirical strategy. As previously discussed, five states experienced statutory changes that allowed some celebrities postmortem publicity rights while withholding them from other observationally similar celebrities based on when, and in what state they died. For most of our analyses we restrict the sample to celebrities who died in the state of New York (statutory change effective in 2021), Alabama (statutory change effective in 2015), Arkansas (statutory change effective in 2016), Hawaii (statutory change effective in 2009,), and Virginia (statutory change effective in 2015). We construct a panel data set where we observe for each individual celebrity 'i' who died in one of these states between 2004 and 2023, annual measures of the various outcome variables previous discussed along with indicators for whether an individual is dead in time 't' and whether they have lost publicity rights (i.e., they are treated) in time 't'. We note again that all celebrities in this subsample have publicity rights prior to their death, but upon death, those in our treatment group lose publicity rights, while those in our control group maintain publicity rights, even after death. For several variables (KWP and some trademark measures) we use cross-sectional data. In those cases we expand the analysis to all 50 U.S. states and measure the conditional differences between celebrities with publicity rights and those without publicity rights.

Our primary analyses use a difference-in-differences framework, where treatment occurs at death for celebrities who are not afforded postmortem publicity rights (because they died prior to the effective data of their state's statutory changes). All celebrities are considered untreated for the time periods in which they are alive, since they all are afforded living publicity rights. Celebrities who are afforded postmortem publicity rights (because they died after an applicable statutory change) are considered untreated in all time periods. Because treatment is necessarily concurrent with a consequential regime change (death) we must also distinguish the bona fide treatment effect from the regime change (death) effect. To achieve this we include an indicator for whether a celebrity is alive in a given period (irrespective of whether they are in our treatment or control group), in addition to the treatment indicator. We also include year and state fixed effects to account for systematic time trends in our outcome variables and otherwise unaccounted for characteristics of a state's legal landscape. Our base model is:

$$Y_{it} = \alpha_s + \gamma_t + \mu Treated_{it} + \lambda Dead_{it} + \beta \mathbf{X_{it}} + \epsilon_{it} \tag{1}$$

Where Y_{it} is the applicable outcome variable (discussed above), α_s and γ_t are, respectively, state and year fixed effects, and X_{it} is the vector of control variables. Treatment effects are measured by μ. In some instances we modify the empirical approach to accommodate certain characteristics of outcome variables. These are discussed in context in subsequent sections.

For our trademark data, we construct binary outcome variables and use the logit estimator.

The remainder of our outcome variables are counts and rates, which are censured at zero and not normally distributed. They also exhibit a high frequency of zeros, with that frequency increasing with time-since-death. For that reason we estimate the model with a zero-inflated Poisson (ZIP) regression. We use the logistic regression based on the time-since-death and the length of a celebrity's name (for reasons discussed below) in the inflation phase of the ZIP estimator.

We also note that as time-since-death increases, the size and composition of the relevant control group changes,[22] thus blunting our measures of long-term treatment effects.[23] For that reason our main analysis is limited to the short-term treatment effects, defined as the year of treatment and the first two years following treatment.[24] Examining short-term effects is also helpful insofar as the post-death bump in popularity gives us richer data with which to examine differences between those in the treatment and control groups. Outside of the post-death bump, and especially in periods long after death, Google searches are relatively infrequent for most celebrities, making comparisons between celebrities somewhat noisy and possibly biased towards zero.[25] The relative increase in popularity for both groups essentially allows us to zoom in on the differences between them. For comparison, estimates of long-term treatment effects, which are likely biased towards zero, are reported in the Appendix.

Lastly, we note an empirical challenge arising from the imperfect way in which we must link data sets. In particular, there is unfortunately no unique identifying code for celebrities; instead we must match based on their names. This produces a non-trivial number of false matches, which adds random noise to our analyses and thus decreasing the precision of our estimates. However, as one might expect, this problem is much more salient for relatively short names compared to longer names. For example, the name "Jon Smith" produces far more false matches than the name "Kareem Abdul-Jabbar." This presents a useful mechanism for reducing the noise caused by false matches. Specifically, we drop all names with fewer than 10 characters, and then weight the remaining observation by the number of characters in the celebrity's name, noting that, on average, longer names have a greater informational value as they are more likely to be true matches.[26]

Our general empirical approach also raises some concerns about endogeneity and other sources of bias in our estimators. These are addressed in Section V with a more detailed discussion in the Appendix.

[22] This is because a celebrity must have died after the statutory change in order to be in the control group, which necessarily excludes long-dead celebrities.

[23] For example, New York changed its statute in 2021, giving us only three years of post-statutory change data. If we were to compare all New York celebrities in the treatment group to those in the control group, we would be comparing people who are between one and 20 years postmortem to people who are between one and three years postmortem.

[24] We limit our measure of the death effect in the same way.

[25] We have an outcome distribution that is censored at zero, and for which many values are zero in time periods long after death. This makes comparison of the treatment and control groups in such periods tenuous. Examining periods where both groups have more values greater than zero helps mitigate this issue.

[26] Using a 10 character cutoff appears to offer the best balance between sample size and false match reduction, but alternative reasonable thresholds produce similar results.

IV Results

Our empirical results as they relate to, 1) celebrity popularity and commercial exploitation of NILs, 2) copyright reliance, and 3) trademark reliance and strategic IPR management in the presence of publicity rights, are reported in Table 3, and discussed below. Alternative specification, diagnostics, and robustness tests are discussed in Section V and the Appendix.

Table 3: Empirical Findings

	(1) Google Search	(2) Cost/ Click	(3) Comp. Index	(4) Copyright Regs.	(5) Copyright Enforc.	(6) TM Regs	(7) Active TM
Treat. Effect/ No PRs	-0.160	0.120	0.037	1.582	2.860	1.314	0.974
	(0.048)	(0.045)	(0.010)	(0.611)	(0.182)	(0.004)	(0.492)
Death Effect	0.249			-1.528	-2.424		-1.379
	(0.057)			(0.612)	(0.175)		(0.586)
Constant	2.960	-2.576	-4.228	-3.712	-1.607	-4.778	-5.618
	(0.004)	(0.018)	(0.001)	(0.827)	(0.150)	(0.006)	(0.083)
Obs.	24,700	147,027	147,027	12,848	14,706	123,392	316,080
Model	DiD	X-sect.	X-sect.	DiD	DiD	X-sect.	DiD
Estimator	ZIP	Poisson	Poisson	ZIP	ZIP	Logit	Logit

Notes: Standard errors (in parentheses) are clustered at the state level. Cross-sectional ("X-sect.") models include celebrities from all 50 U.S. states and control for death-year fixed effects. DiD models include celebrities from the five states in which a statutory change occurred; the models also include state and year fixed effects, as well as death effects. For reasons previously discussed, both the death effect and treatment effect cover the first two years after the year of death. ZIP models use a logistic link function for the inflation phase of the model. Inflation coefficient estimates omitted for brevity.

We start with measures of popularity and commercial activity, as represented by Google search volume (column (1) of Table 3), Google's price for advertising in association with celebrity NILs (column (2)), and the competition between advertisers who wish to do so (column (3)). The treatment effect on Google search volume is negative and strongly significant, indicating that the loss of publicity rights causes a 15% reduction in popularity,[27] and suggesting a reduction in the commercial activity (and value) around NILs. Said differently, celebrities who are eligible for postmortem publicity rights tend to become more popular and enjoy greater commercial value of their NILs after death when compared to similar celebrities who lose publicity rights at death.

With respect to the KWP metrics in columns (2) and (3), we find that the lack of publicity rights is associated with a 13% higher advertising cost (cost-per-click) and 4% more intense competition among advertisers for the ability to advertise in association with a celebrity's NIL.[28] Said differently, when celebrities have publicity rights, there tends to be less competition for keywords related to their NILs and the cost-per-click that the winning bidder must pay is lower. These results may seem counterintuitive at first blush, but are in fact consistent with the express goal of intellectual property: reduced competition for the incentivizing benefit of rightsholders. Moreover, the results

[27] $15\% = e^{-0.160} - 1$.

[28] $13\% = e^{0.12} - 1$. $4\% = e^{0.037} - 1$.

suggest that publicity rights have measurable commercial value to rightsholders and meaningfully influence market behavior.

Next we turn to the relationship between publicity rights and reliance on copyright. As previously discussed, we use two distinct measures of copyright reliance: copyright registrations (column (4)) and DMCA takedown notices (column (5)). Our estimated treatment effect on copyright registrations is positive and significant, indicating that the loss of publicity rights causes a 386% increase in copyright registrations.[29] Similarly, our estimated treatment effect on DMCA takedown notices is positive and significant, indicating that the loss of publicity rights causes a 1,646% increase in copyright enforcement.[30] These substantial increases in copyright registrations and enforcement imply that the publicity rights and copyrights are indirect substitutes, and the loss of the former increases reliance on the latter. Moreover, the magnitude of the treatment effects suggests that publicity rights have significant commercial value.

Additionally, we note that the difference in magnitude between registrations and enforcement is likely an artifact of the diminishing supply of works eligible for registration after treatment. Recall that treatment happens upon death; thus, a treated creator is necessarily not producing any more copyright-eligible works. The postmortem registrations we do observe are for works produced during the creator's life and registered for copyright by their estate after their death. In contrast, the supply of works that can be the subject of a DMCA takedown notice remains constant after a celebrity dies.[31] For that reason, in the specific context of our empirical design, DMCA takedown notices likely provide a more accurate indicator of changes in copyright reliance than do registrations.

Finally, we examine the relationship between publicity rights and reliance on trademark protection, as reported in columns (6) and (7). In column (6) we alter our empirical methodology to accommodate characteristics of our data. The relevant factor is that we identify trademarks specifically related to a celebrity's name, and in that respect, almost every celebrity in our sample has exactly zero or one trademark registration during their life, although those trademark registrations can be renewed *ad infinitum*, so long as they are appropriately used and maintained. Thus, our analysis in column (6) steps away from panel data methods and instead aggregates over time for a cross-sectional analysis. In particular, using celebrities from all US states, we measure the conditional relationship between not having publicity rights and a celebrity's decision to register at least one trademark. The outcome variable is 1 if celebrity 'i' has ever registered such a trademark and 0 otherwise. The results indicate a positive and highly significant relationship, such that the unavailability of publicity rights is associated with a substantially larger probability of registering a trademark. In particular, the average conditional predicted probability of registering a trademark is 2.5% for those with publicity rights and 8.6% for those without publicity rights, meaning that

[29] $386\% = e^{1.582} - 1$.

[30] $1,646\% = e^{2.86} - 1$.

[31] Works created after 1978 are typically under copyright protection in the U.S. for 70 years after the author dies.

celebrities without publicity rights tend to register trademarks related to their names at more than three times the rate of celebrities with publicity rights.

One should, however, exercise caution in attributing a causal interpretation to the results in column (6). A causal relationship between publicity rights and trademarks seems highly plausible given that there is meaningful direct overlap in what the two forms of IPRs cover, our empirical design, in the particular case of column (6), can not rule out endogeneity. While our inclusion of state and death-year fixed effects accounts for many of the omitted variables that one might expect to influence the relationship, we have no source of exogenous variation. Thus, the relationship may be, in part, the result of endogenous sorting between states (e.g., celebrities that benefit more from publicity rights than from trademarks moving to jurisdictions that afford them those rights). However, we note that, as further discussed in Section V, these results are robust to the exclusion of states where one might most expect endogenous sorting to be a concern (i.e., New York and California).

Although we find these results reassuring, they still do not fully rule out endogenous sorting. For that reason, we return to panel data and a difference-in-differences approach in column (7) of Table 3. In this model we compare the outcome variable to an indicator for whether a celebrity lacks publicity rights in a given year. However, because trademark registration tends to be a singular event (at least for the types of trademarks in our sample) we change the outcome variable from having at least one registered trademark at any point in time, to having an *active* trademark in a given year. For this exercise, as with our other DiD analyses, we limit the sample to only those celebrities who live in one of the five states that saw statutory changes with respect to postmortem rights.

A trademark registration has an initial term of 10 years, after which it can be renewed for additional fees as many times as the owner wishes in 10 year increments (so long as certain conditions are met). Additionally, a trademark claim can be affirmatively relinquished at any time or it can be passively relinquished by the rightsholder failing to take action at the end of a term. We consider a trademark to be active in a given year if, 1) that year is after the initial registration, 2) the year is not more than 10 years after the registration or latest renewal, and 3) the trademark has not been affirmatively relinquished prior to that year. One limitation to this approach is that it results in rather coarse time increments. If, for example, a rightsholder chooses to abandon their trademark claim, we may observe the result immediately if they choose to affirmatively relinquish it, but if the trademark is passively relinquished through a failure to renew, it also could be up to 10 years before that fact is reflected in the data. While this issue is unlikely to be a source of bias, it does add significant noise to the data, reducing the precision with which we can estimate the treatment effects.

Nevertheless, the estimated causal effect of losing publicity rights on trademark reliance (column (7)) remains positive and weakly significant, consistent with our cross-sectional analysis discussed above. The average conditional predicted probability of having an active trademark in year 't' is 0.6% for those with publicity rights and 1.6% for those without publicity rights. This, again, indicates that celebrities without publicity rights tend to rely on trademarks related to their names at about three times the rate of celebrities with publicity rights. Thus, losing publicity rights appears to substantially increase the probability that a celebrity will rely on trademark protection, implying that the dominant relationship between the two types of IPRs is substitutional.

V Empirical Concerns and Robustness

Before considering the implications of our analyses, we first address potential empirical concerns (with further discussion and robustness tests presented in the supplemental Appendix). One key concern in constructing our empirical strategy is of endogenous sorting between states. That is, celebrities may select their state of residence (and the state in which they intend to die) based on relevant statutory considerations. As the anecdotal evidence shows, some individuals choose their location for a variety of strategic reasons, such as tax optimization. This selection leads to certain problems in identifying the causal relationships of interest. As previously discussed, our exploitation of changes in relevant state laws and inclusion of state fixed effects at least partially controls for this possibility in our DiD design. It is unlikely that celebrities will quickly relocate after postmortem rights are implemented in a different state for several reasons.

First, relocating often takes substantial time, and the decision to do so may take even longer. Second, there are likely much more influential factors that determine the state in which a celebrity will choose to live as they near death, such as estate tax regimes and the location of family and friends. Finally, and perhaps most convincingly, if postmortem publicity rights are a sufficiently meaningful determinant of where one chooses to live, there are many states that have, for decades, made postmortem rights available. If, for instance, a celebrity wished to move to a state with postmortem rights, they could have moved to, say, California, at any time; there is little need for them to wait for Alabama or Virginia to change their laws, and then relocate to one of those states. In the longer run one might expect that established legal regimes with respect to publicity rights may affect celebrities location on the margin, but, again, this seems unlikely in the short-term.

While it seems unlikely that endogenous sorting meaningfully affects our DiD treatment effect estimates, it may be a more salient concern for our cross-sectional analyses where most states established their publicity laws long ago, allowing sufficient time for endogenous sorting. Nonetheless, in order to partially mitigate this issue, we also re-estimate all of our cross-sectional models after dropping the states where endogenous sorting is most likely to be of concern (California and New York). These results are consistent with (although in some cases less significant than) our main results reported in Table 3. Also, we note that in the case of trademark reliance, our cross-sectional results are consistent with our DiD results. Similarly, we compare our KWP cross-sectional results to our DiD results. KWP provides a measure of online popularity that is separate from the Google Trends metric previously discussed. We compare estimates for that cross-sectional KWP popularity metric with the DiD popularity metric (results reported in the Appendix) and find the cross-sectional results to be highly consistent with the DiD results, lending further credibility to the cross-sectional analyses. As reported in the Appendix, our difference-in-differences result implicate a −14.8% treatment effect and our cross-sectional results show that the lack of publicity rights is associated with a −13.5% difference in popularity. Additionally, the similarity of these findings speaks to the external validity of our results, noting that our difference-in-differences analyses are based on celebrities in five states and look exclusively at changes in *postmortem* publicity rights, while our cross-sectional analyses are based on all U.S. states and look at *all* publicity rights (for living and deceased celebrities).

Separate from endogenous sorting, a related concern is that of reform endogeneity. For example, one of the main results we discuss in the previous section is that once celebrities are afforded postmortem protections, they become less reliant on copyright protection after death relative to those who died before the reform. Our interpretation of this result (discussed in the next section) is that celebrities are able to adjust their business-models to accommodate the slate of IPRs available to them. However, an alternative explanation could be that the composition of celebrities in a state may change prior to the statutory change, such that the average celebrity in that state is relatively more reliant on publicity rights compared to copyrights (or trademarks). This could explain both the statutory reform and the relative changes in copyright and publicity right reliance. Our primary empirical strategy does control for this to some extent insofar as treatment occurs at death (if death occurs before the reform) and not necessarily at the time of the reform; thus, we are comparing individuals' behavior to their own pre-death behavior as well as to the behavior of others who are not yet treated or are never treated. However, all the individuals that are treated (i.e., they lost publicity rights at death) died before reform and all those who are never treated (in our control group) died after reform. So it is still possible that our results could be driven by changes over time in the types of celebrities who reside in a state.

If this were the case, we should see fewer celebrities of the type that one might expect to be more reliant on copyright and more of the type one might expect to be primarily reliant on publicity rights in the time leading up to the reform, and then continuing after the reform. We test for this in two ways. First, we use state-level occupations data and examine employment levels in relevant occupations over time. Second, we look at the composition of celebrities in our dataset in the five target states over time. In both cases the results (reported in the Appendix) are inconsistent with the sort of compositional change that would lead to reform endogeneity.

Yet another concern is the correlation between popularity and age as a potentially confounding factor to the analysis. Putting aside the measurement-related downward trend in Google search volume over time discussed in Section III.B, in practice, more recently dying cohorts of celebrities tend be more popular than celebrities dying before them, as shown in previous research (Waldfogel, 2012). So, in theory, estimates of popularity might be biased by the fact that celebrities granted postmortem rights after their death are typically more popular than older cohorts that are not granted rights in the same state, simply by the virtue of them being alive more recently. Our inclusion of year fixed effects partially addresses this issue since we are comparing across states which implemented statutory changes in different years. To further address this issue, we also control for years since death (which ranges from -20 to 20) in our ZIP specifications.

A separate concern is the estimation bias that can arise in two-way fixed effect (TWFE) difference-in-difference models when treatment is staggered over time. Recent literature has documented these issues (e.g., Borusyak et al. (2021); Baker et al. (2022)). We address them econometrically by implementing multiple versions of estimators proposed by Sun and Abraham (2021); Sun (2022); De Chaisemartin and d'Haultfoeuille (2020); Borusyak et al. (2024); Callaway and Sant'Anna (2021); Goodman-Bacon (2021) to account for possible issues caused by the nature of staggered treatment adoptions and the necessity of homogeneity in the treatment in the classical two-way fixed effects models. Additionally, we perform a battery of placebo tests on our data. The results are reported in the Appendix. Both suggest that our TWFE DiD models produce unbiased and consistent estimates.

Finally, we further consider the common trends assumption for our DiD models. Notably, our placebo test results and dynamic DiD estimators are both consistent with common trends between our treatment and control groups. As a final test of the assumption we measure the degree of divergence between pre-treatment trends in the treatment group and pre-death trends in the control group. Significant divergence in pre-trends would indicate a likely violation of the common trends assumption, whereas little or no divergence is consistent with the assumption. Our tests regress outcome variables on a relative time trend (relative to celebrity 'i's year of death) and an interaction between the time trend and the treatment group indicator. A significant coefficient on the latter indicates pre-trend divergence. Results are reported in Table A.8 of the Appendix. In all cases the pre-trend divergence between the treatment and control groups is not statistically different than zero, and is numerically close to zero, consistent with common pre-trends.

VI Discussion

Our results provide important insights for IPR strategy and policy on several fronts: 1) the effect of publicity rights on a celebrity's popularity and the role of publicity rights in facilitating commercial activity; 2) the relationship between publicity rights and copyright reliance; and 3) the relationship between publicity rights and trademark reliance.

We find that losing publicity rights results in decreased popularity. While our data does not provide insights into the exact mechanisms that drive this change, two obvious potential candidates are decreased promotion by a celebrity's estate and less intense exploitation of the persona. The result is also consistent with the conceptual framework we develop based on business model flexibility. If a celebrity elects to adopt a more persona-centric business model, it is likely they will invest more in promoting that persona, with the goal of increasing popularity. If such a business model becomes less attractive or unavailable due to the loss of publicity rights, some will shift towards a less persona-centric business model, requiring less investment in promoting their persona, thus leading to a reduction in popularity.

In that way, this finding also serves as indirect evidence of a relationship between publicity rights and commercial activity. This is because popularity can be both an indicator and driver of commercial activity. Increased commercial activity will likely lead to more Google searches, thus increasing our measure of popularity. At the same time, popularity is significant determinant of the demand for celebrity-related goods and services.

Relatedly, our results vis-à-vis KWP metrics suggest that, as intended, publicity rights are associated with reduced competition related to celebrity NILs. We observe that a lack of publicity rights correlates with a higher cost-per-click advertising cost and more advertisers bidding for a search term associated with a celebrity. This suggests that celebrities with publicity rights have a measurably greater opportunity to monetize their NILs. While this would logically lead to increased control and commercial activity through channels owned or authorized by the rightsholder, it also implicates a reduction in commercial activity from unauthorized third parties consistent with prior research on the effects of rights expiry (Reimers, 2019; Morton, 2000). The net impact of these countervailing factors is an empirical question for further research. However, to the extent Google search volume typically has an increasing monotonic relationship with total persona-related commercial activity (from both authorized and authorized sources), our evidence implies that the net effect of publicity rights on total commercial activity is positive. This means that the positive incentivizing effect of publicity rights for rightsholders outweighs the negative restricting effect on commercial activity from unauthorized channels.

In most markets we expect the relationship between competition and output to be positive. The idea that increased competition (as measured by the KWP metrics) is associated with decreased output (proxied by persona popularity) in the case of NIL exploitation is, however, consistent with Schumpeterian competition, which is core to the economic justification for IPRs. In particular, theory and evidence around Schumpeterian competition indicate that the relationship between competition and output follows an inverted-U pattern such that competition will increase output in previously low-competition markets, but decrease output for already high competition markets (Aghion et al., 2015). This is because, while firms facing competition feel pressure to innovate in order to remain competitive, they also have reduced incentives to invest in innovation because the competition reduces the innovation-related gains that can be captured by the innovator. Intellectual property is intended to help industries on the downward slopping portion of the competition/output curve achieve more socially efficient outcomes. IPRs (which intentionally reduce competition) would be inefficient if applied to industries on the upward sloping portion of the curve. The negative relationship between competition and commercial activity observed in our data implies that markets for persona-related commerce are on the downward sloping portion of the curve. As such, competition-reducing IPRs like publicity rights can increase efficiency, producer surplus and, possibly, total welfare, thus suggesting that the economic justification for IPRs may hold for publicity rights. However, we should note that a negative relationship between competition and output is a necessary, but not sufficient condition for restricted competition to be welfare improving.

With respect to other IPRs, we find that there is a strong substitutional relationship between publicity rights and copyright reliance, and between publicity rights and trademark reliance. Generally, our findings suggest that for the subset of celebrities who do or can produce valuable copyrightable works, copyright and trademarks can serve as (possibly indirect) substitutes for publicity rights. While the publicity rights and NIL-related trademarks do have substantive overlap in what they can be applied to, the same is generally not true for publicity rights and copyrights. However, even though these two types of rights do not directly protect the same content, they do both, to some extent, offer mechanisms for the indirect appropriation of value. However, this differs somewhat from the type of indirect appropriability first discussed by Liebowitz (1985). In Liebowitz's example, academic periodical publishers who typically license to academic institutions were able to appropriate the value of unauthorized copying by downstream users (researchers) because that value factored into the derived demand of the institution, increasing their willingness to pay for a subscription. If we think of this as vertical indirect appropriation, then what we observe in our data could be characterized as a sort of horizontal indirect appropriation, where some of the value of one thing (e.g., copyrighted works) can be captured by the sale of a related thing (e.g., the persona). This is closely related to Teece (1986)'s notion of value appropriation through complimentary assets.

The indirect substitutability of IPRs has several related, but subtle, policy implications. First, it means that the effects of contemplated policy changes towards publicity rights will be substantially dampened by the compensating behavior of rightsholders. For example, when offering broader publicity rights, the increased social welfare will likely not reflect the full gross value of those rights, because many rightsholders are already compensating for the lack of publicity rights through greater copyright and trademark reliance. Once they have publicity rights they would likely shift away from those other IPRs, to some extent. The second, related implication is that if new digital and AI technologies erode the strength of copyright protection, strengthening alternative means for appropriating the value of creative works, such as through stronger publicity rights, can mitigate this effect and enable rights holders to continue to benefit from their investments.

However, as a cautionary note, this does not suggest that copyright and trademark protection can perfectly compensate for a lack of publicity rights. As a preliminary matter, many celebrities do not primarily produce copyrightable works. For example, Michael Jordan has been able to monetize his persona by writing several books, but that revenue stream is likely several orders of magnitude smaller than what he earned by licensing his likeness to Nike (a deal that may have looked much different absent publicity rights). It is unlikely that, without NIL protection, Jordan would have been able to compensate for lost Nike revenue through his literary publishing deals. Moreover, even for those celebrities who do primarily create copyrightable works, the relevant IPRs are likely not perfect substitutes for one another. Thus, the loss of publicity rights may not be able to be compensated for by any degree of copyright protection. Even the broadest possible copyright protection on Elvis' music is unlikely to make up for the revenues generated through the direct exploitation of his public persona.

More generally, our findings suggest strategic under-enforcement of certain IPRs when rightsholders have multiple IPRs from which to choose. The fact that rightsholders, upon losing publicity rights, can and do switch to heavier copyright or trademark reliance, implies that those rightsholders had a greater capacity for enforcing those IPRs than they were previously exercising. This confirms that, unsurprisingly, the profit maximizing level of enforcement for a given IPR can be less than full enforcement even when the cost of enforcement is minimal, and, importantly, it is a function of other available IPRs.

VII Conclusion

This article provides the first empirical examination of publicity rights and causal evidence on their economic effects in the digital age, addressing a significant gap in the literature. By exploiting asynchronous changes in U.S. state laws regarding postmortem publicity rights, the research can inform the strategic management of NIL assets and new policy development in the area, particularly in light of emerging technologies such as artificial intelligence and digital replicas.

Our findings show how publicity rights interact with various other forms of intellectual property protection, as well as their impact on celebrity popularity and commercial activities. We demonstrate that the loss of publicity rights leads to decreased celebrity popularity, indirectly suggesting a decline in commercial activity. This aligns with our conceptual framework, which posits that the availability of publicity rights influences business model choices and flexible investment in persona vis-à-vis the promotion of creative works. Additionally, we observe a strong substitutional relationship between publicity rights and copyright/trademark reliance, indicating that rightsholders strategically shift between different forms of intellectual property protection. Overall results, derived from two-way fixed effects difference-in-differences models, prove to be quite robust.

Our main findings have important ramifications for strategic intellectual property management and policy development. They show that rightsholders can adapt their strategies and business models in response to changes in publicity rights policies, potentially dampening the impact of such policy changes. Our findings also suggest strategic under-enforcement of certain IPRs when rightsholders have multiple options, implying that the profit-maximizing level of enforcement for a given IPR can be less than full enforcement and is a function of other available IPRs. This research lays the groundwork for future research on the economic aspects of NIL assets and publicity rights, particularly in the context of evolving digital technologies and artificial intelligence. Further investigation into the mechanisms driving these relationships and their long-term implications for asset management and intellectual property policy is warranted.

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Appendix: Alternative Specifications and Additional Robustness Tests

A Alternative Specifications

While the ZIP and logit estimators presented in Section IV are conceptually best suited for our data and empirical models, we have also tested alternative estimators, to include Poisson and ordinary least squares (OLS), which produce results consistent with those in Section IV. Additionally, we have estimated both long- and short-term treatment effects, noting that the former are likely bias towards zero for the reasons discussed in Section C. We also report the mostly inconclusive results from our analyses of Google Shopping and YouTube data.

We start with results relating to the effect of publicity rights on popularity (as measured by Google search volume), commercial activity (as measured by YouTube and Google Shopping search volumes), advertising value of NILs, and related competition (as measured by KWP metrics). Our estimation results related to general Google search trends are reported in Table A.1. We include OLS, Poisson, and ZIP model estimates for the long-term treatment effect (in odd-numbered columns) as well as for short-term treatment effects (in even-numbered columns).

Table A.1: Treatment Effects on Google Searches

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson	(5) ZIP	(6) ZIP
Treatment-Effect	-0.249		-0.262		-0.118	
	(0.093)		(0.108)		(0.137)	
Treatment-Effect (Short-Term)		-0.116		-0.147		-0.160
		(0.053)		(0.041)		(0.048)
Death-Effect	0.198		0.274		0.106	
	(0.104)		(0.119)		(0.154)	
Death-Effect (Short-Term)		0.269		0.240		0.249
		(0.064)		(0.060)		(0.057)
Constant	1.748	1.710	2.242	2.244	2.967	2.960
	(0.012)	(0.003)	(0.011)	(0.004)	(0.009)	(0.004)
R^2/Psuedo	0.15	0.15	0.12	0.11	.	.
Root MSE	0.95	0.95	1.20	1.20		
Obs.	26,360	26,360	26,360	26,360	24,700	24,700

Notes: Standard errors (in parentheses) are clustered at the year and state level. All models include state and year fixed effects. Treatment and Death effects, unless otherwise noted, cover all periods after death or treatment. Short-term effects cover the first two years after death or treatment. The dependent variable for Columns 1 & 2 is ln(Google Search Volume + 1). Dependent variable for Column 3-6 is Google Search Volume. ZIP models use a logistic link function for the inflation phase of the model. Inflation coefficient estimates omitted for brevity.

The long-term treatment effect is consistently negative, but either not significant or only weakly so. However, the short-term treatment effect is negative and, in the case of the Poisson and

ZIP estimators, strongly significant. It is unclear whether the relative difference between those in treatment and control groups shrinks over time or if it is merely our ability to measure the difference that diminishes over time. Nonetheless, it seems clear that the loss of publicity rights has a meaningful negative effect on a celebrity's popularity.

Table A.2 reports our model estimates using YouTube search volume as the outcome variable, and Table A.3 reports our model estimates using Google Shopping search volume as the outcome variable. As can be seen, in both cases the sign of the estimated treatment effect is invariably negative, making the results directionally aligned and consistent with our general Google search volume results. However, the estimates have little statistical significance. Indeed, only model 2 of the Google Shopping results is significant at the 0.05 level. While these results do not preclude the possibility of a direct effect on commercial activity, it seems clear that YouTube and Google Shopping are not particularly robust channels of commercialization for the celebrities in our sample.

Table A.2: Treatment Effects on YouTube Searches

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson	(5) ZIP	(6) ZIP
Treatment-Effect	-0.062		-0.027		-0.017	
	(0.055)		(0.097)		(0.127)	
Treatment-Effect (Short-Term)		-0.119		-0.077		-0.039
		(0.029)		(0.053)		(0.072)
Death-Effect	0.068		0.087		0.074	
	(0.071)		(0.107)		(0.128)	
Death-Effect (Short-Term)		0.130		0.100		0.079
		(0.030)		(0.058)		(0.069)
Constant	1.753	1.756	2.190	2.218	2.794	2.802
	(0.022)	(0.000)	(0.020)	(0.002)	(0.007)	(0.006)
R^2/Psuedo	0.25	0.25	0.16	0.16	.	.
Root MSE	0.84	0.84	1.10	1.10		
Obs.	20,176	20,176	20,176	20,176	18,645	18,645

Notes: Standard errors (in parentheses) are clustered at the year and state level. All models include state and year fixed effects. Treatment and Death effects, unless otherwise noted, cover all periods after death or treatment. Short-term effects cover the first two years after death or treatment. The dependent variable for Columns 1 & 2 is ln(YouTube Search Volume + 1). Dependent variable for Column 3-6 is YouTube Search Volume. ZIP models use a logistic link function for the inflation phase of the model. Inflation coefficient estimates omitted for brevity.

We now turn to our Google Key Word Planner results. For this analysis we are limited to cross-sectional data since Google only provides metrics for the most recent 12 month period. We have three outcome variables of interest. The first is Google search volume. This differs from the previously discussed search volume metric taken from Google Trends insofar as it provides the raw number of searches for a given search term as opposed to the normalized relative index value provided by Google Trends. The Second outcome variable we use is the "Cost per Click". This is how much an advertiser must pay Google every time a Google user clicks on an advertisement

Table A.3: Treatment Effects on Google Shopping Searches

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson	(5) ZIP	(6) ZIP
Treatment-Effect	-0.043		-0.158		-0.043	
	(0.048)		(0.118)		(0.065)	
Treatment-Effect (Short-Term)		-0.040		-0.029		-0.021
		(0.054)		(0.067)		(0.059)
Death-Effect	0.031		0.157		0.031	
	(0.045)		(0.119)		(0.068)	
Death-Effect (Short-Term)		0.041		0.054		0.056
		(0.051)		(0.067)		(0.056)
Constant	1.426	1.420	1.720	1.724	2.479	2.473
	(0.002)	(0.002)	(0.007)	(0.001)	(0.012)	(0.009)
R^2/Psuedo	0.18	0.18	0.15	0.15	.	.
Root MSE	0.78	0.78	0.99	0.99		
Obs.	19,793	19,793	19,793	19,793	18,301	18,301

Notes: Standard errors (in parentheses) are clustered at the year and state level. All models include state and year fixed effects. Treatment and Death effects, unless otherwise noted, cover all periods after death or treatment. Short-term effects cover the first two years after death or treatment. The dependent variable for Columns 1 & 2 is ln(Google Shopping Search Volume + 1). Dependent variable for Column 3-6 is Google Shopping Search Volume. ZIP models use a logistic link function for the inflation phase of the model. Inflation coefficient estimates omitted for brevity.

that appears in the search results for the given search term. It is based on bids from advertisers. The third outcome variable is Google's "Competition Index." While Google does not reveal the exact formula for this metric, it asserts that the metric reflects the number of advertisers bidding on a search term and the intensity of competition between them.

Using these outcome variables, we conduct an analysis on all U.S. states using an indicator for whether an individual has or had publicity rights (based on the state in which they live). Results are reported in columns (1)-(3) of Table A.4. There is no source of exogenous variation in who has rights in this framework, thus we cannot control for endogenous sorting between states. Nonetheless, in order to partially mitigate this issue, we also conduct the analysis after dropping the states where this is most likely to be of concern (California and New York). These results are reported in Columns (4)-(6) of Table A.4.

The results indicate that not having publicity rights is quite strongly associated with lower Google Search volumes (columns (1) and (4)). Our cross-sectional results using the KWP search volume metric are highly consistent with our difference-in-differences results using the Google Trends search volume metric. The former indicates that no publicity rights is associated with a 13.5% decrease in search volume and the latter indicates a 14.8% decrease.[32] In addition to validating the consistency of our cross-sectional analyses, the similarity of these findings also speaks to the external validity of our results, noting that our difference-in-differences analyses are based

[32] $13.5\% = e^{-0.145} - 1$ (see column (1) of Table A.4). $14.8\% = e^{-0.16} - 1$ (see column (6) of Table A.1).

Table A.4: Relationship Between Publicity Rights and Keyword Planner Metrics

	(1) Search Vol.	(2) Cost/Click	(3) Comp. Idx.	(4) Search Vol.	(5) Cost/Click	(6) Comp. Idx.
No Pub. Rights	-0.145	0.120	0.037	-0.080	0.095	0.020
	(0.042)	(0.045)	(0.010)	(0.024)	(0.042)	(0.011)
Constant	7.730	-2.576	-4.228	7.676	-2.529	-4.213
	(0.040)	(0.018)	(0.001)	(0.020)	(0.025)	(0.000)
Psuedo R^2						
Obs.	147,027	147,027	147,027	112,831	112,831	112,831

Notes: Standard errors (in parentheses) are clustered by death year and state. All estimates based on cross-sectional data. Estimated using Poisson. Columns 1-3 include all US states and columns 4-6 drop California and New York. All models include death year fixed effects. ”Search Volume” is the number of Google searches conducted for a specific search term during 2023. It differs from previous measures of Google search volume insofar as here, we have the raw number of searchers rather than a relative index value. ”Cost/Click” reflects how much Google charges for every click by a user on an advertisement link associated with the search term. The Competition Index” reflects the competition level for advertisement spots associated with the search term.

on celebrities in five states and look exclusively at changes in *postmortem* publicity rights, while our cross-sectional analyses are based on all U.S. states and look at *all* publicity rights (for living and deceased celebrities).

As discussed in Section IV, the results in columns (2) and (3) of Table A.4 are consistent with the express goal of intellectual property: reduced competition for the benefit of rightsholders. The results indicate that the lack of publicity rights, despite leading to lower search volumes, is associated with a higher cost per click (columns (2) and (5)) and a higher level of advertiser competition for a search term (columns (3) and (6)).

We now turn to copyright reliance, our estimation results for copyright registrations and DMCA takedown notices are respectively reported in Table A.5 and Table A.6. We report OLS, Poisson, and ZIP model estimates for the long-term treatment effect (in odd-numbered columns) as well as for short-term treatment effects (in even-numbered columns).

For copyright registrations, we consistently see positive treatment effects (the effect of losing publicity rights), both in terms of the long-term and short-term effects. The results are mainly significant, aside from column (1), and indicate that when a celebrity loses publicity rights, they tend to register more copyrights compared to similar celebrities who retain publicity rights. This, in turn, implies an increased reliance on copyright protection. The smaller and slightly less significant long-term treatment effects on copyright registrations are to be expected for the reasons discussed in Section C. Our results With respect to DMCA takedown notices are consistent with the effects on registrations. They reveal positive and strongly significant short-term effects, but no significant long-term effects.

Taken together, the evidence suggests that when celebrities lose publicity rights, they (or their estates) become more reliant on copyright protection. This effect is highly pronounced in the short-term, but becomes more tenuous in the long-term. Again, it is unclear if the effect is truly short-lived or if the long-term results merely reflect a hampered ability to measure the effect long

Table A.5: Treatment Effects on Copyright Registrations

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson	(5) ZIP	(6) ZIP
Treatment-Effect	0.021 (0.016)		0.842 (0.403)		1.222 (0.404)	
Treatment-Effect (Short-Term)		0.042 (0.014)		1.355 (0.586)		1.582 (0.611)
Death-Effect	-0.042 (0.013)		-1.041 (0.342)		-1.017 (0.352)	
Death-Effect (Short-Term)		-0.039 (0.016)		-1.320 (0.582)		-1.528 (0.612)
Constant	0.083 (0.002)	0.072 (0.000)	-1.536 (0.041)	-1.644 (0.002)	-3.757 (0.806)	-3.712 (0.827)
R^2/Psuedo	0.02	0.02	0.05	0.05	.	.
Root MSE	0.28	0.28	4.86	4.84		
Obs.	13,651	13,651	12,848	12,848	12,848	12,848

Notes: Standard errors (in parentheses) are clustered at the year and state level. All models include state and year fixed effects. Treatment and Death effects, unless otherwise noted, cover all periods after death or treatment. Short-term effects cover the first two years after death or treatment. The dependent variable for Columns 1 & 2 is ln(Copyright Registrations + 1). Dependent variable for Column 3-6 is Copyright Registrations. ZIP models use a logistic link function for the inflation phase of the model. Inflation coefficient estimates omitted for brevity.

after death (because of the previously discussed limits to our data and empirical design).

Finally, we turn to the relationship between publicity rights and reliance on trademark protection, as reported in Table A.7. In addition to columns (1) and (3), results previously discussed in Section IV, as a robustness check, column (2) replicates the analysis in column (1) after dropping celebrities from New York and California. This is intended to compensate for the fact that the cross-sectional analysis in column (1) may be the result of endogenous sorting between states. New York and California are the states where we would most expect this to be an issue. The fact that columns (1) and (2) produce highly similar results increases our confidence that endogenous sorting is not a significant driver of our cross-sectional results.

Table A.6: Treatment Effects on DMCA Takedown Notices

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson	(5) ZIP	(6) ZIP
Treatment-Effect	0.011		-0.983		-0.911	
	(0.021)		(0.735)		(0.753)	
Treatment-Effect (Short-Term)		0.046		3.304		2.860
		(0.010)		(0.405)		(0.182)
Death-Effect	-0.013		0.651		0.556	
	(0.024)		(0.718)		(0.705)	
Death-Effect (Short-Term)		-0.032		-2.574		-2.424
		(0.009)		(0.269)		(0.175)
Has Copyright Registrations	0.054	0.054	2.290	2.338	0.919	0.970
	(0.009)	(0.010)	(0.226)	(0.232)	(0.253)	(0.217)
Constant	0.016	0.013	-1.299	-1.663	-1.439	-1.607
	(0.005)	(0.005)	(0.131)	(0.161)	(0.247)	(0.150)
R^2/Psuedo	0.03	0.03	0.24	0.25	.	.
Root MSE	0.30	0.30	11.08	11.01		
Obs.	15,480	15,480	12,384	12,384	14,706	14,706

Notes: Standard errors (in parentheses) are clustered at the year and state level. All models include state and year fixed effects. Treatment and Death effects, unless otherwise noted, cover all periods after death or treatment. Short-term effects cover the first two years after death or treatment. The dependent variable for Columns 1 & 2 is ln(DMC Takedowns + 1). Dependent variable for Column 3-6 is DMC Takedowns. ZIP models use a logistic link function for the inflation phase of the model. Inflation coefficient estimates omitted for brevity.

Table A.7: Relationship Between Rights of Publicity and Trademark Protection

	(1) Has TM	(2) Has TM	(3) Has Active TM in 't'
No Pub. Rights	1.314	1.312	
	(0.004)	(0.005)	
No Pub. Rights in Year 't'			0.974
			(0.492)
Is Dead in Year 't'			-1.379
			(0 (0.586)
Constant	-4.788	-4.774	-5.618
	(0.004)	(0.007)	(0.083)
Fixed Effects	ST/DY	ST/YR	ST/DY
Psuedo R^2	0.008	0.009	0.014
Obs.	123,392	94,422	316,080

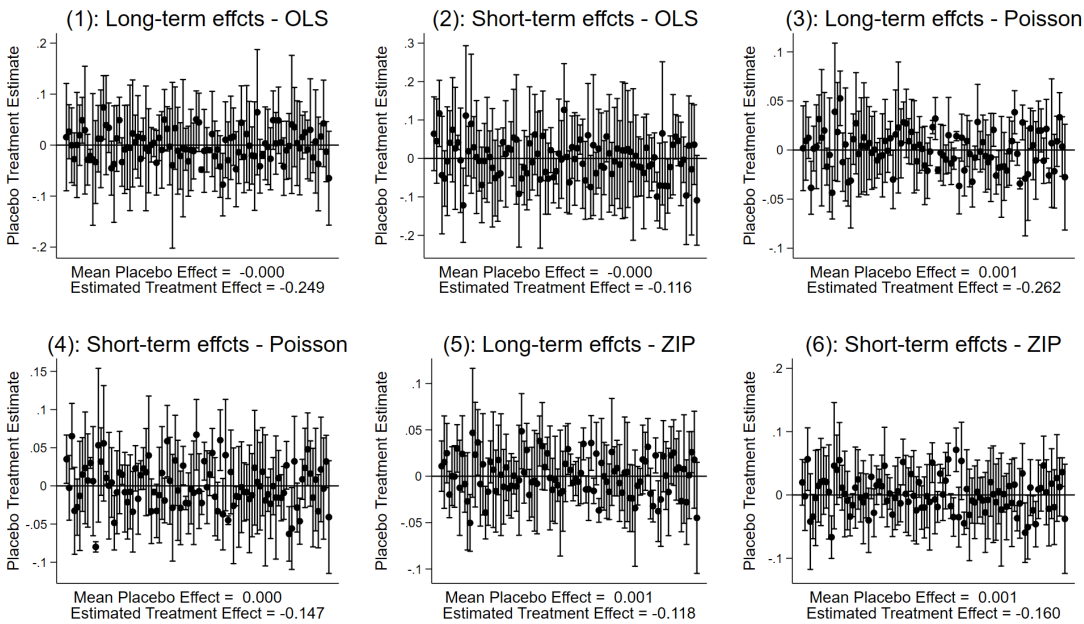
Notes: Standard errors (in parentheses) are clustered at the state level. All estimates based on a logit model where the respective outcome variables are binary. Columns (1) and (2) estimated using cross-sectional data and predict the probability of a celebrity having at least one trademark registered during their life based on whether the celebrity lives in a state with publicity rights. Column (1) includes celebrities in all US states, whereas column (2) drops New York and California. Columns (3) estimated on panel data with observations at the celebrity/year level for years 2004 through 2023. It predicts the probability that celebrity 'i' will have an active trademark in year 't' based on whether they have publicity rights in year 't'. The sample is restricted to only those celebrities who live in a state that experienced a legal change with respect to postmortem publicity rights. All models include state fixed effects. Models (1) and (2) also include death year fixed effects and model (3) includes year fixed effects, in addition to an indicator for whether the celebrity is dead in year 't'.

B Robustness Tests

In this section we report the results of a battery of robustness tests, to include placebo tests, dynamic difference-in-difference estimators, pre-trend tests of the common trends assumption of our difference-in-differences models, and tests for reform endogeneity. We first turn to our placebo tests. We conducted these tests in two ways. For the first set, we construct randomized, fictitious outcome values and re-estimate the treatment effects for all models in Section IV. For the second set, we randomly assign individuals to either the treatment or control group, and once again re-estimate the treatment effect. For both sets, we estimate the model 100 times, randomizing either the outcome or the treatment indicator for each instance. The results are reported in Figures A.1 through A.14. Each figure corresponds with a regression table in the previous section, and each panel within a figure corresponds with a column in the associated regression table.

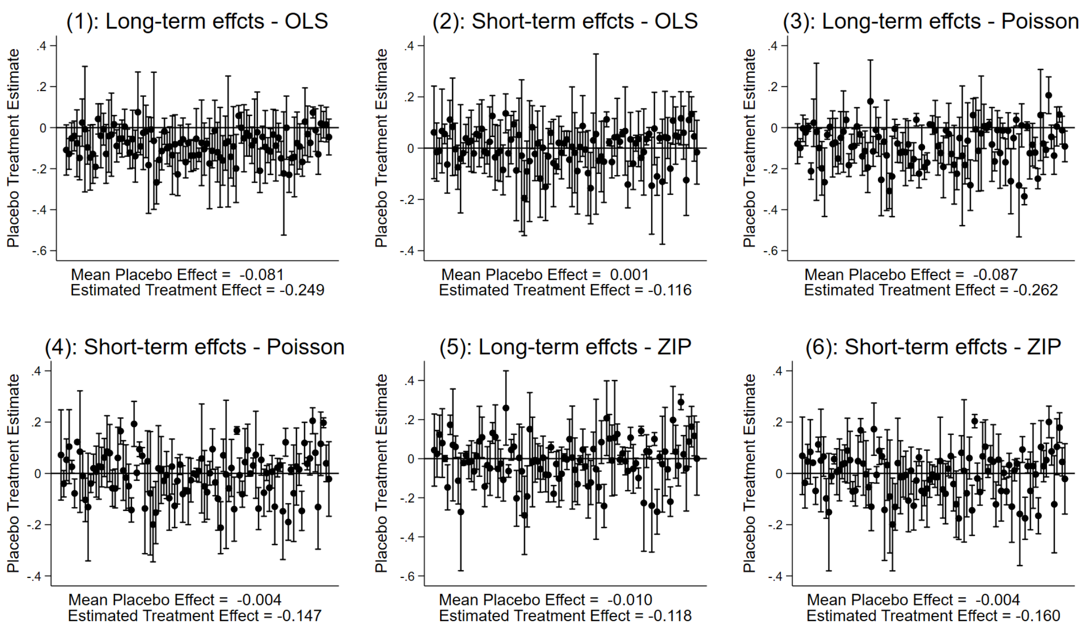
In most cases our placebo tests indicate that our models are well-specified and consistent with unbiased estimators. However, several specifications do appear to produce a degree of bias. Figure A.2, panels (1) and (3): These specifications measure the long-term treatment effect on Google search volume using OLS and Poisson, respectively. The results of the placebo tests imply that these specifications slightly overstate the magnitude of the treatment effect. Notably, subtracting the bias implied by the placebo tests from the OLS or Poisson estimated treatment effects results in a treatment effect roughly equal to that produced by our ZIP model in panel (5), which does not show signs of bias. This validates the ZIP model as our preferred specification. Figure A.12, panels (4) and (6): These specifications measure the short-term treatment effect on DMCA takedown notices. The results of the placebo tests imply that these specifications overstate the magnitude of the treatment effect by about 1/3. Nonetheless, the estimated treatment effects remain highly significant even after accounting for the apparent bias.

Figure A.1: Placebo Tests on Google Search Volume - Randomized Outcome



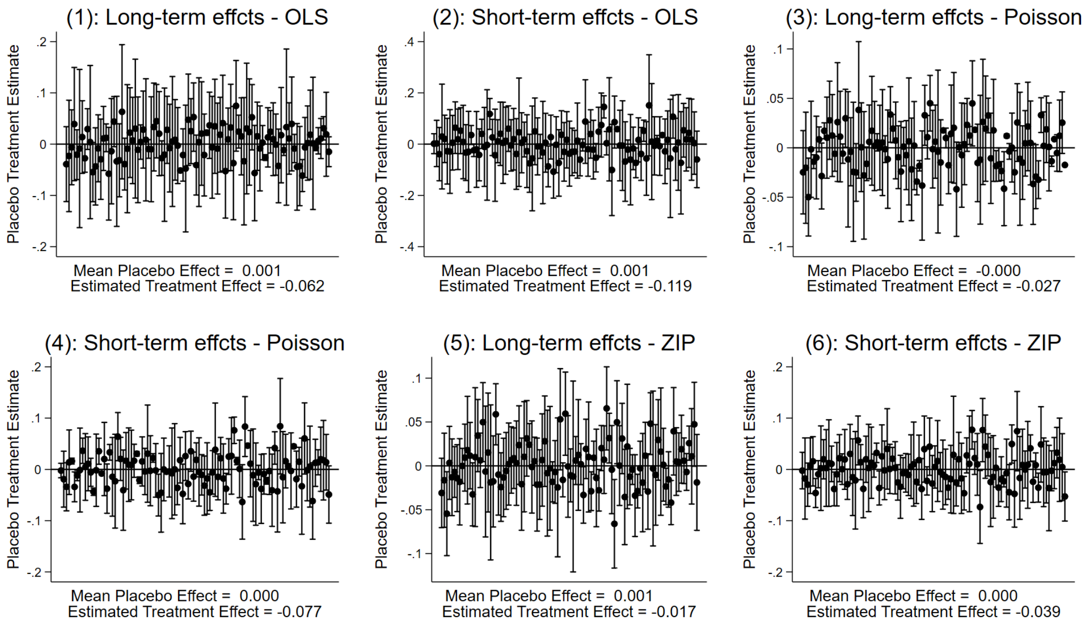
Note: Each panel reports placebo effects for the corresponding model in Table A.1. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

Figure A.2: Placebo Tests on Google Search Volume - Randomized Treatment



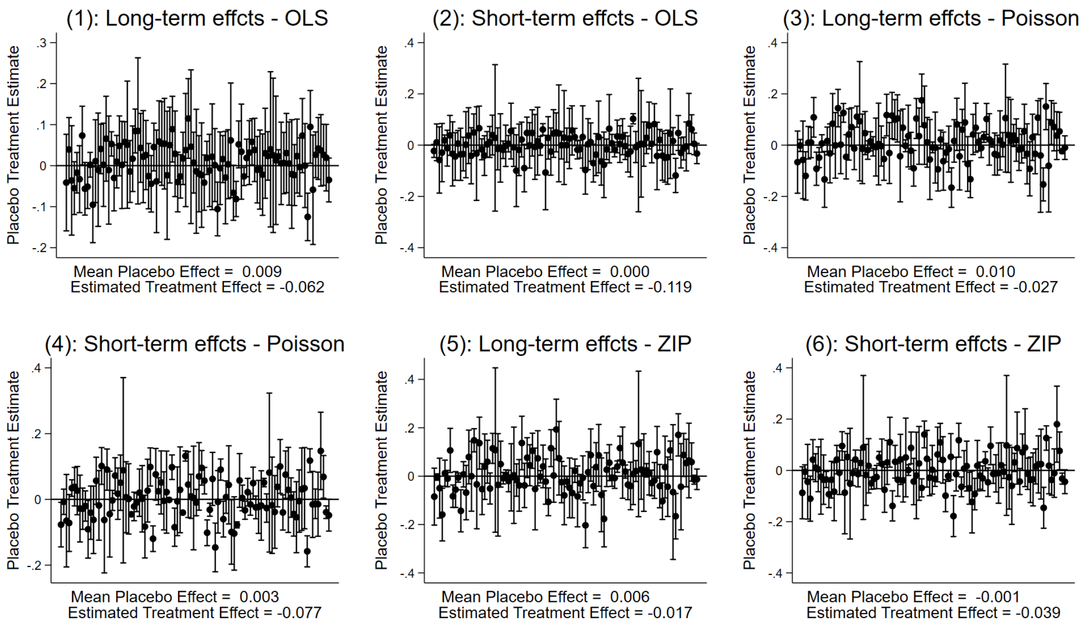
Note: Each panel reports placebo effects for the corresponding model in Table A.1. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

Figure A.3: Placebo Tests on YouTube Search Volume - Randomized Outcome



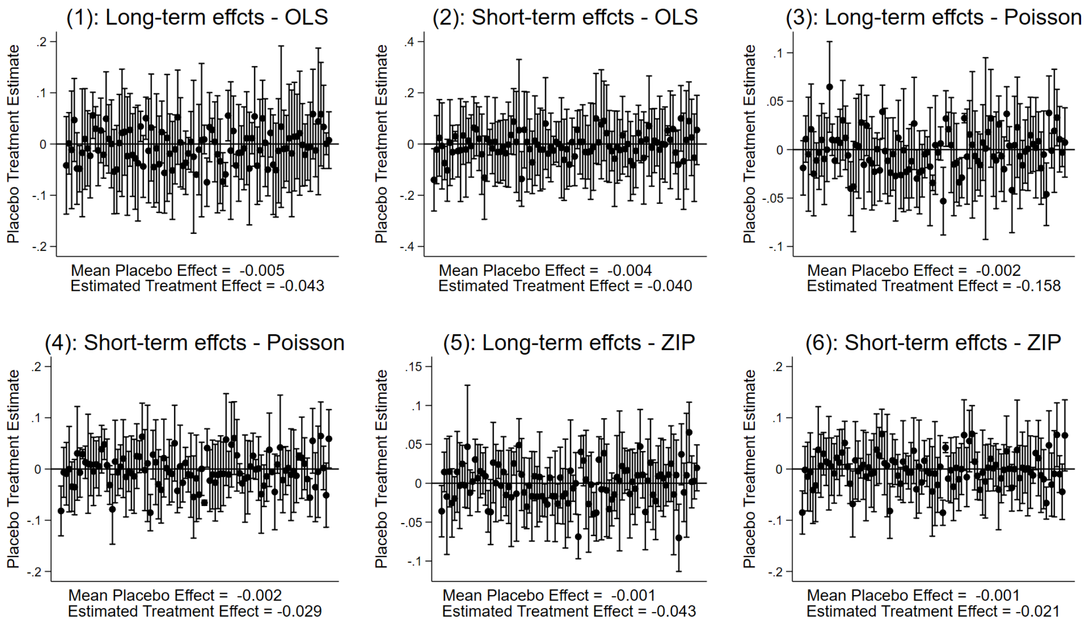
Note: Each panel reports placebo effects for the corresponding model in Table A.2. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

Figure A.4: Placebo Tests on YouTube Search Volume - Randomized Treatment



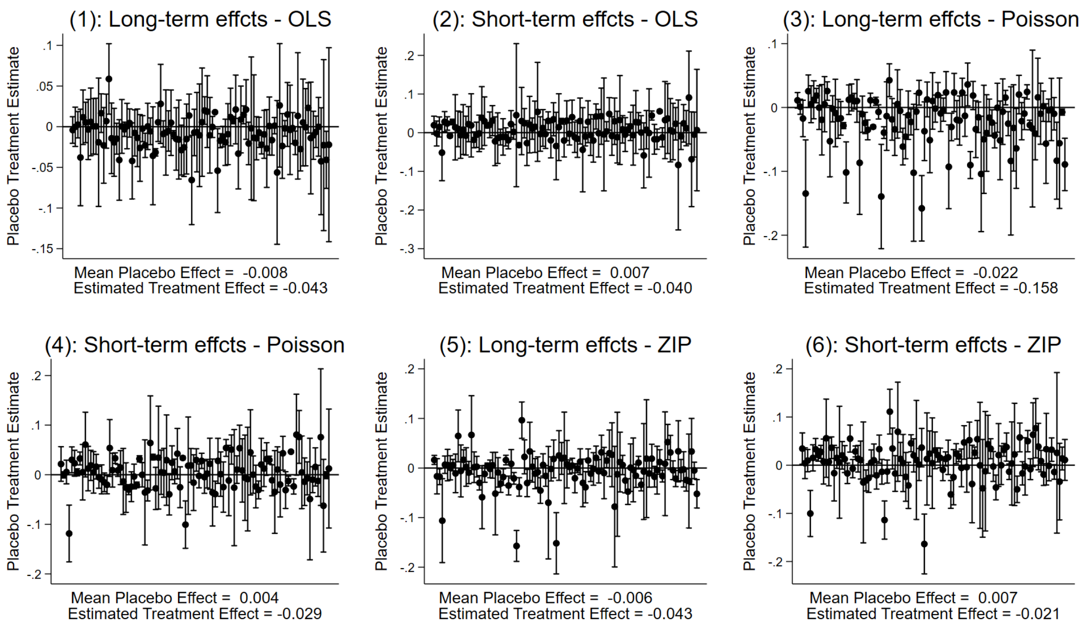
Note: Each panel reports placebo effects for the corresponding model in Table A.2. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

Figure A.5: Placebo Tests on Google Shopping Search Volume - Randomized Outcome



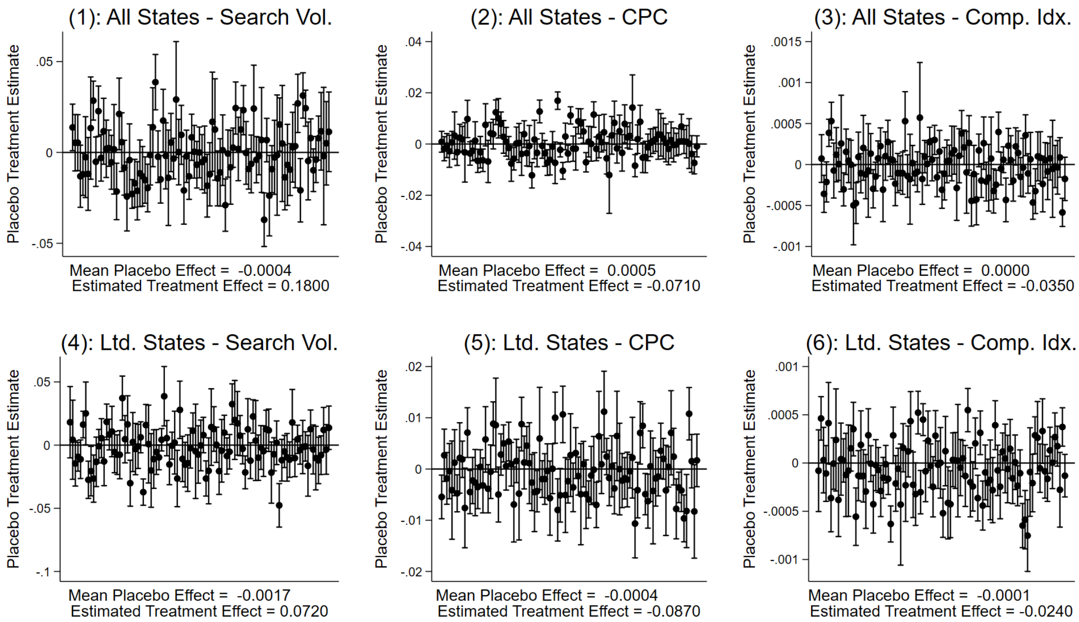
Note: Each panel reports placebo effects for the corresponding model in Table A.3. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

Figure A.6: Placebo Tests on Google Shopping Search Volume - Randomized Treatment



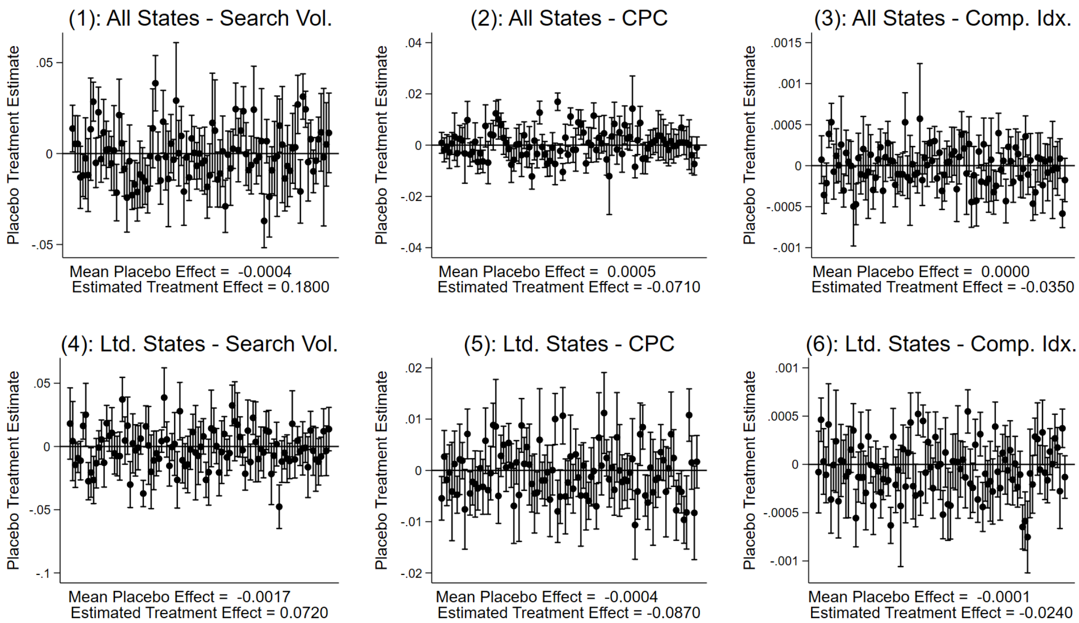
Note: Each panel reports placebo effects for the corresponding model in Table A.3. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

Figure A.7: Placebo Tests on KWP Metrics - Randomized Outcome



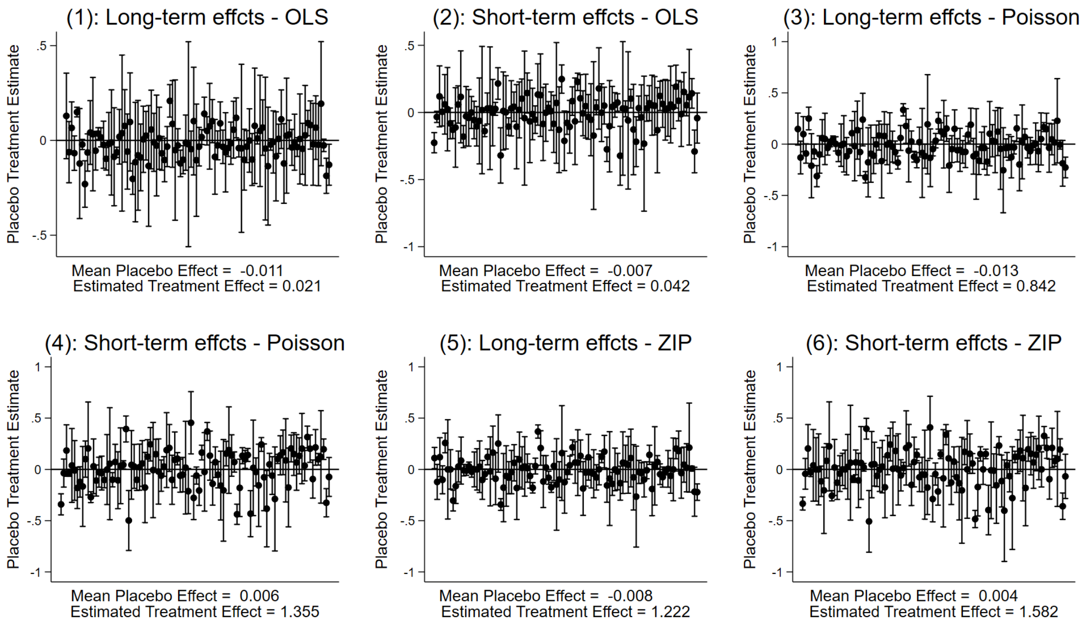
Note: Each panel reports placebo effects for the corresponding model in Table A.4. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

Figure A.8: Placebo Tests on KWP Metrics - Randomized Treatment



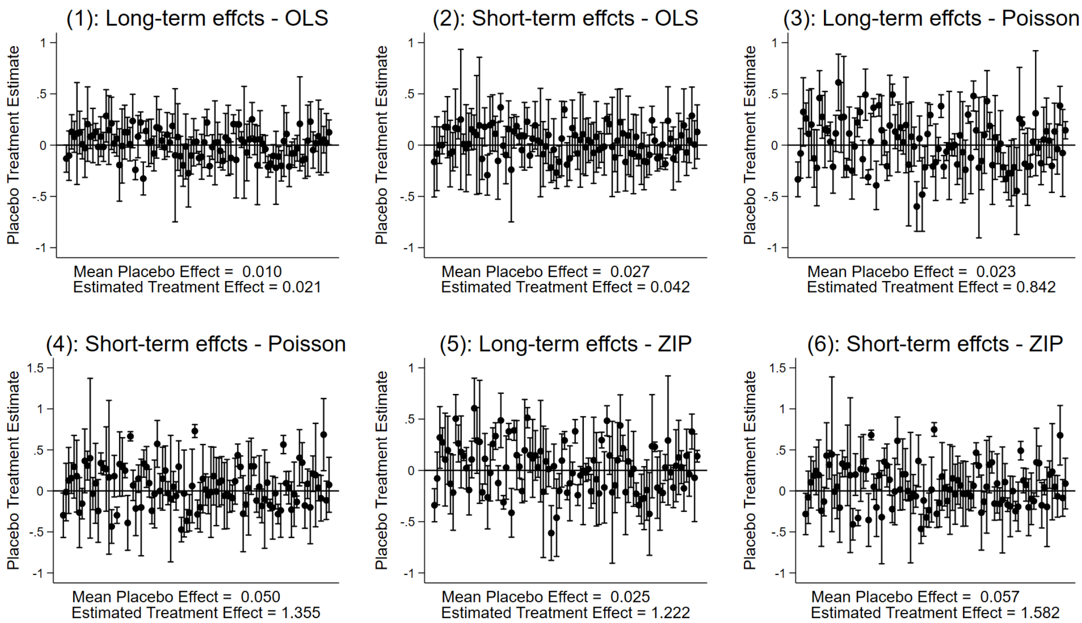
Note: Each panel reports placebo effects for the corresponding model in Table A.4. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

Figure A.9: Placebo Tests on Copyright Registrations - Randomized Outcome



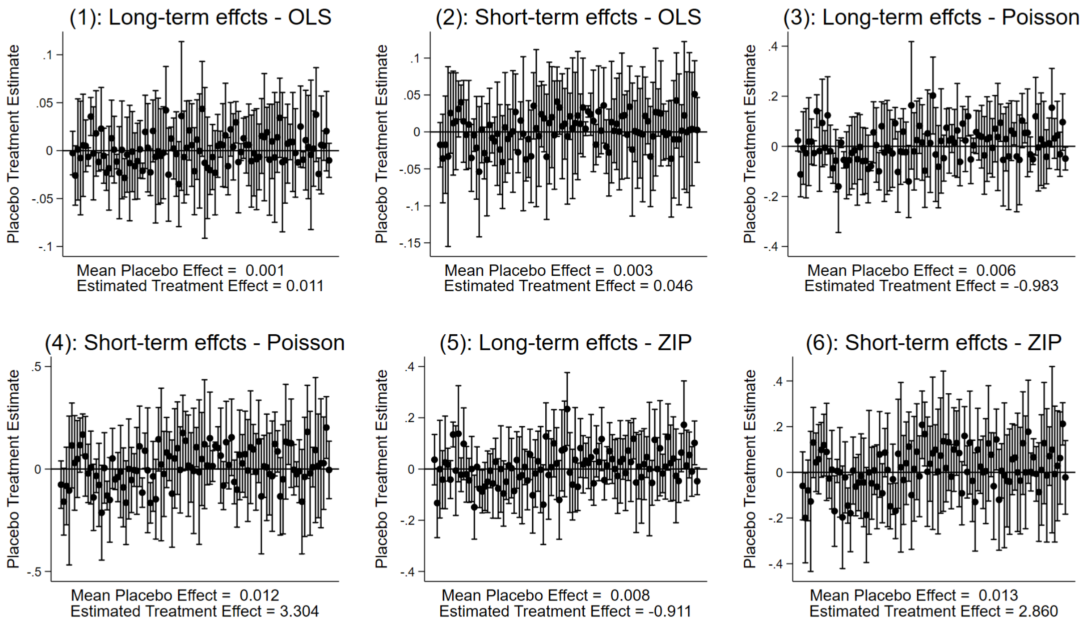
Note: Each panel reports placebo effects for the corresponding model in Table A.5. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

Figure A.10: Placebo Tests on Copyright Registrations - Randomized Treatment



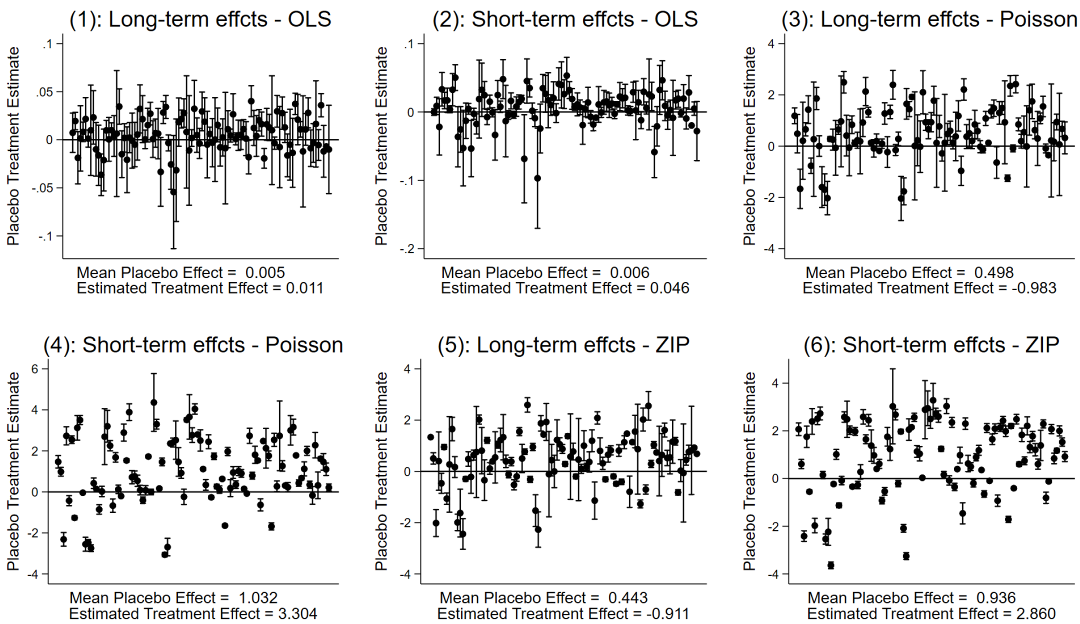
Note: Each panel reports placebo effects for the corresponding model in Table A.5. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

Figure A.11: Placebo Tests on DMCA Takedown Notices - Randomized Outcome



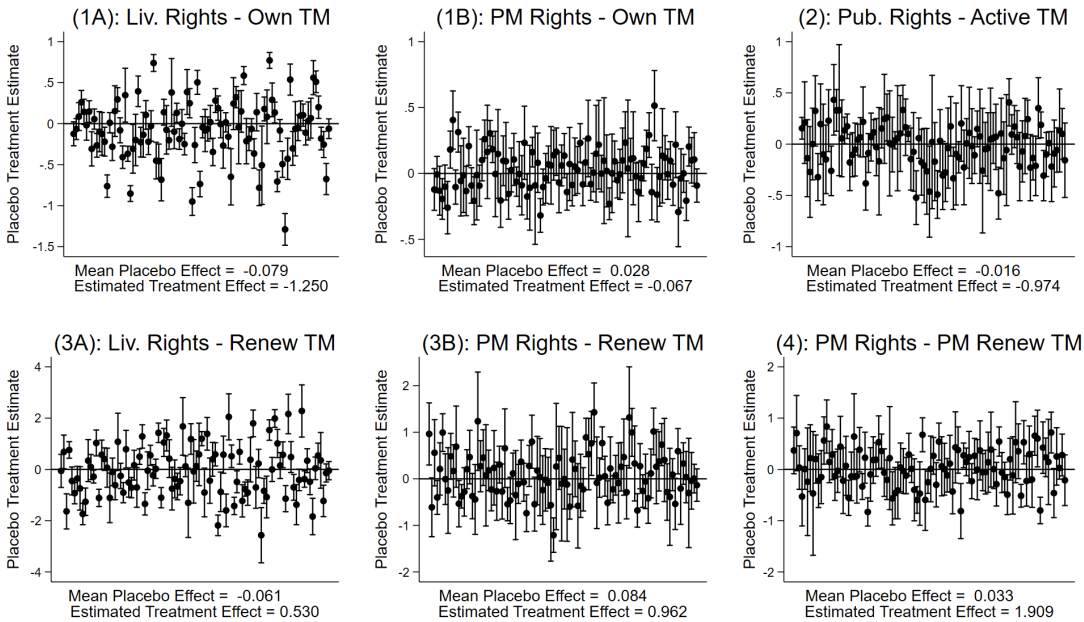
Note: Each panel reports placebo effects for the corresponding model in Table A.6. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

Figure A.12: Placebo Tests on DMCA Takedown Notices - Randomized Treatment



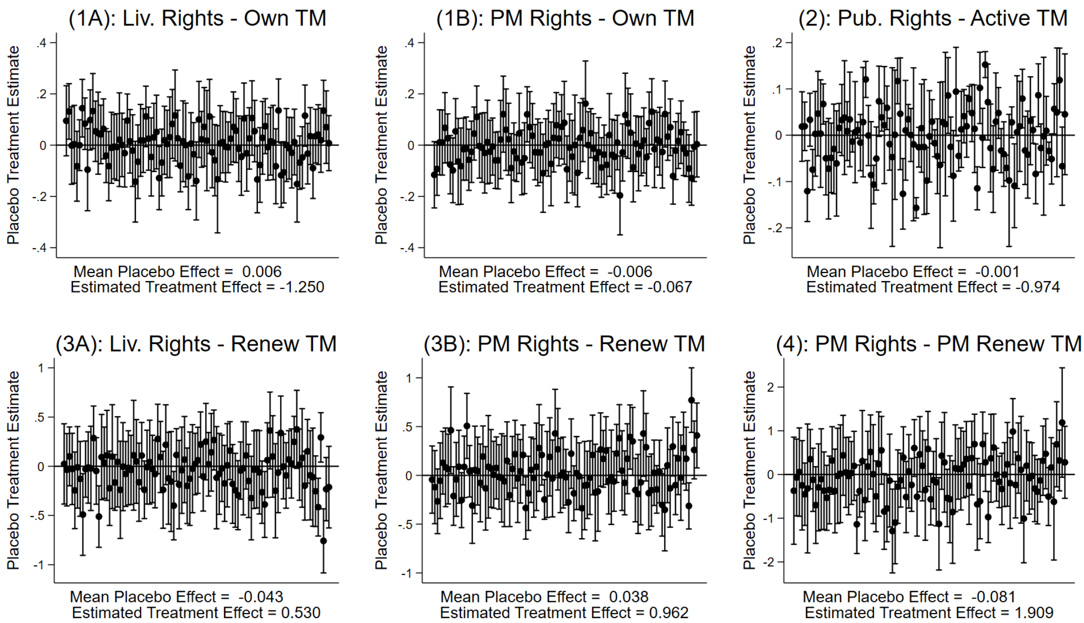
Note: Each panel reports placebo effects for the corresponding model in Table A.6. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

Figure A.13: Placebo Tests on Trademark Activity - Randomized Outcome



Note: Each panel reports placebo effects for the corresponding model in Table A.7. For each model, 100 placebo tests were conducted with fictitious outcomes randomly drawn from the distribution of true outcomes.

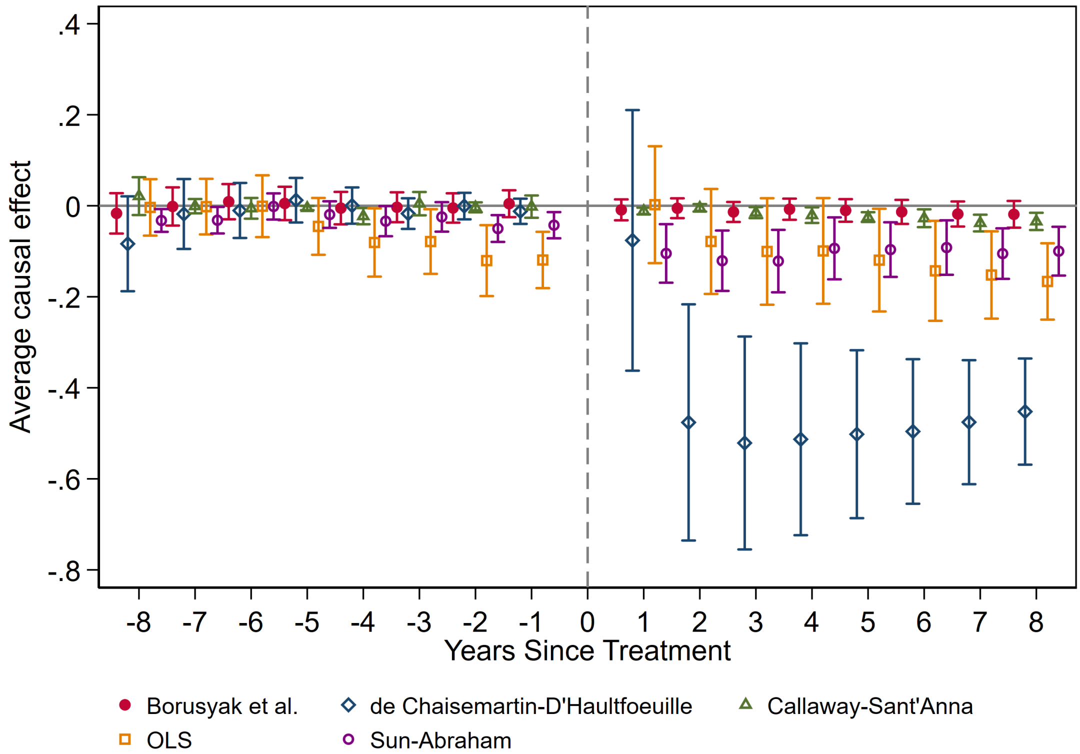
Figure A.14: Placebo Tests on Trademark Activity - Randomized Treatment



Note: Each panel reports placebo effects for the corresponding model in Table A.7. For each model, 100 placebo tests were conducted with fictitious treatment indicators randomly drawn from to match the distribution of true treatment indicators.

We now turn to our set of dynamic DiD tests. Recent literature has addressed issues related to the treatment homogeneity requirement (e.g., Borusyak et al. (2021); Baker et al. (2022)), which we address econometrically by implementing multiple versions of estimators proposed by Sun and Abraham (2021); Sun (2022); De Chaisemartin and d'Haultfoeuille (2020); Borusyak et al. (2024); Callaway and Sant'Anna (2021); Goodman-Bacon (2021) to account for possible issues caused by the nature of staggered treatment adoptions and the necessity of homogeneity in the treatment in the classical two-way fixed effects models. The results, as reported in the following figures, or consistent with our TWFE DiD models reported in Section IV.

Figure A.15: Dynamic Diff-in-Diff Estimators - Google Search Volume



We next consider the common trends assumption for our DiD models. Notably, our placebo test results and dynamic DiD estimators are both consistent with common trends between our treatment and control groups. As a final test of the assumption we measure the degree of divergence between pre-treatment trends in the treatment group and pre-death trends in the control group. Significant divergence in pre-trends would indicate a likely violation of the common trends assumption, whereas little or no divergence is consistent with the assumption. Our tests regress outcome variables on a relative time trend (relative to celebrity 'i's year of death) and an interaction between the time trend and the treatment group indicator. A significant coefficient on the latter indicates pre-trend divergence. Results are reported in Table A.8. In all cases the pre-trend divergence between the

Figure A.16: Dynamic Diff-in-Diff Estimators - Google Shopping Search Volume

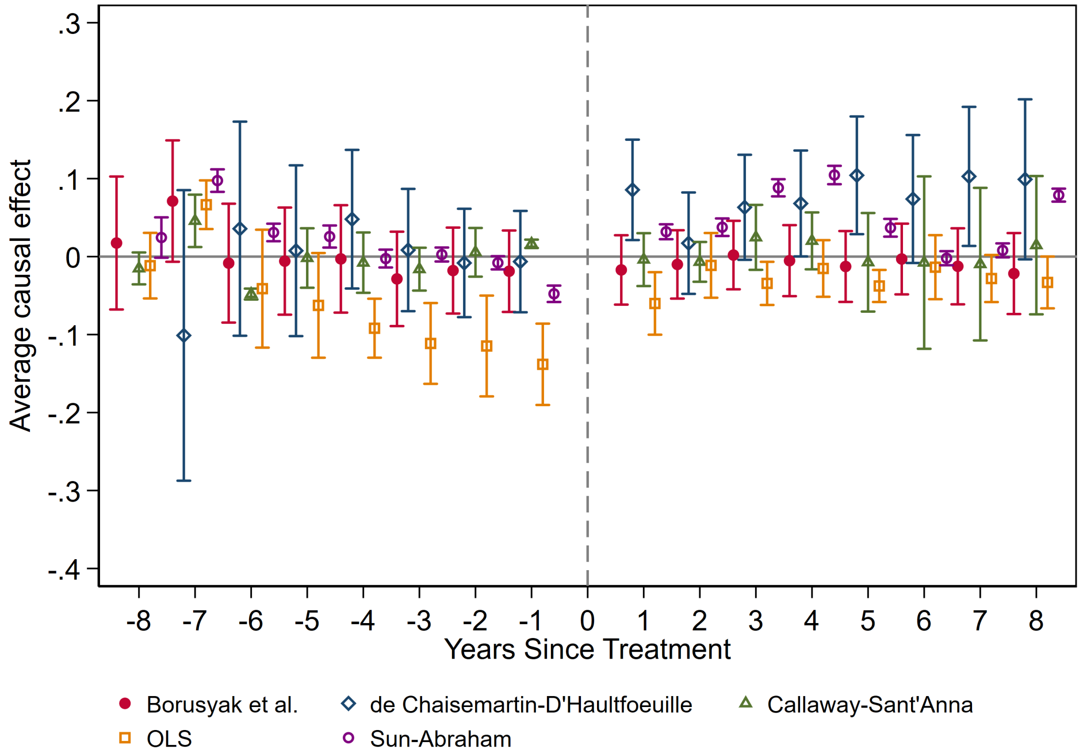


Figure A.17: Dynamic Diff-in-Diff Estimators - YouTube Search Volume

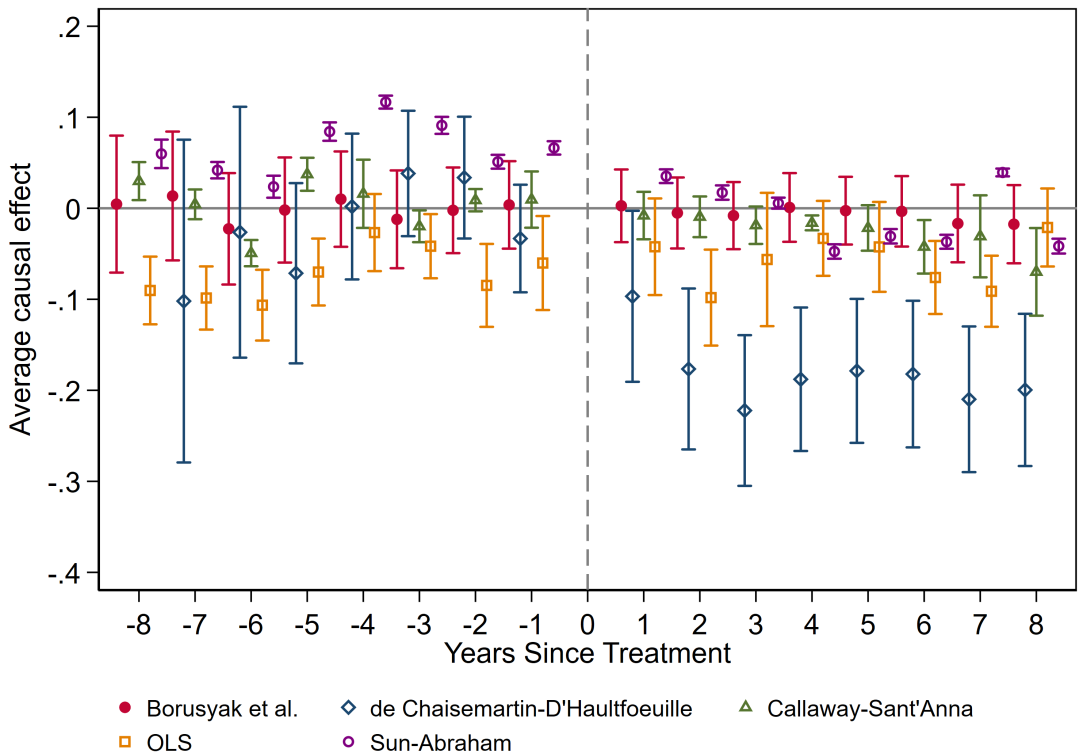


Figure A.18: Dynamic Diff-in-Diff Estimators - Copyright Registrations

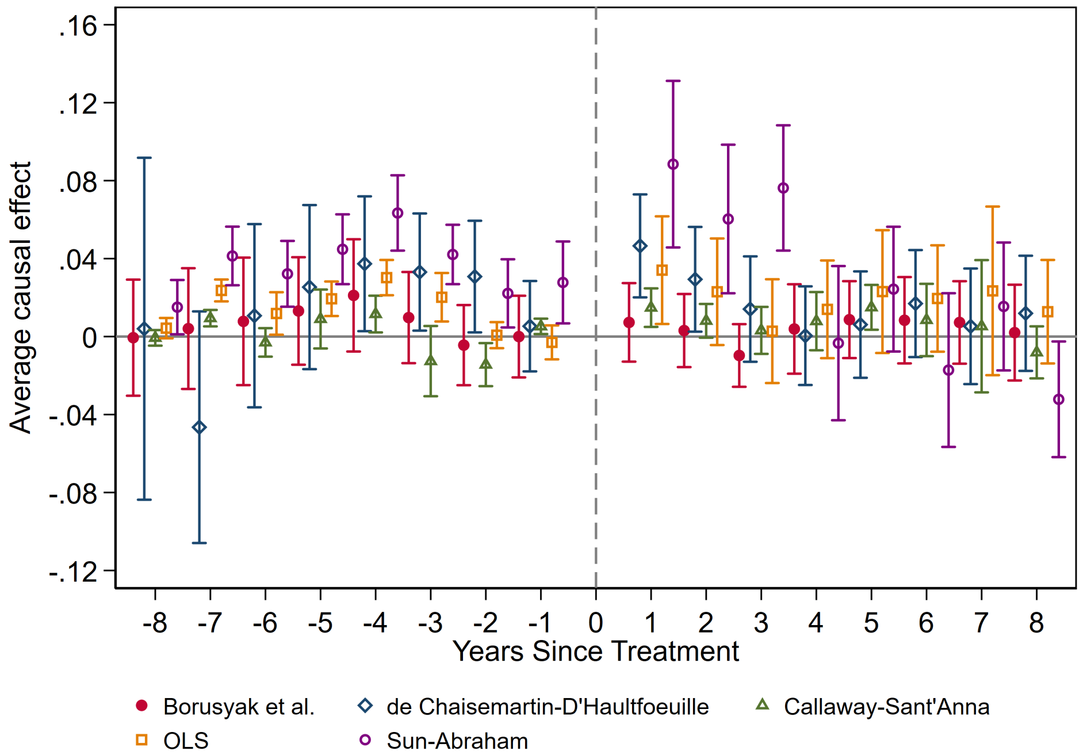


Figure A.19: Dynamic Diff-in-Diff Estimators - DMCA Takedown Notices

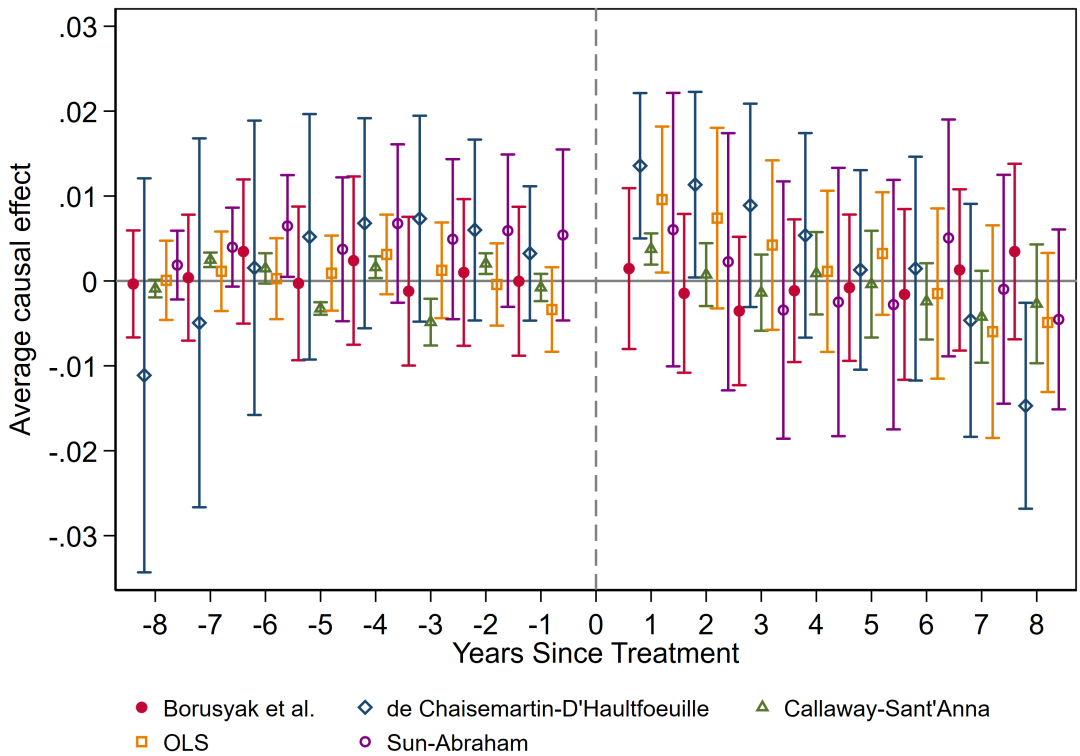


Table A.8: Pre-trend Differences Between Control and Treatment Groups

	(1) Google Search Vol.	(2) Copyright Registrations	(3) Copyright Enforcement	(4) Has Active TM in *'t'*
Time Trend	-0.007	0.028	0.393	0.027
	(0.003)	(0.029)	(0.016)	(0.054)
Time Trend × Treat Grp.	-0.005	-0.023	-0.013	0.008
	(0.004)	(0.018)	(0.016)	(0.080)
Constant	2.883	-5.788	-4.237	-5.127
	(0.031)	(0.573)	(0.146)	(0.203)
Psuedo R^2	0.065	0.092	0.386	0.013
Obs.	10,842	6,276	6,085	21,669

Notes: This table reports the results of pre-trend consistency tests for panel models. The tests measure the degree to which the trends within the treatment group prior to treatment differ from the trends within the control group prior to a celebrity's death. Time trends are represented as the number of years until death (the point in time when those in the treatment group are treated), ending in the year of death for celebrity *'i'*. The estimates for 'Time Trend' represent the trends that are common to the control and treatment groups, whereas the estimates for 'Time Trend x Treatment Grp.' represent any difference in time trends between the control and treatment groups. Non-zero values for the interaction term would indicated differential pre-trends, indicating a likely violation of the common trends assumption for difference-in-differences models. Values close to zero are consistent with the common trends assumption. Columns (1) - (3) report Poisson estimators and column (4) reports the logit estimator. All models include state and year fixed effects. Standard errors (in parentheses) are clustered at the state level.

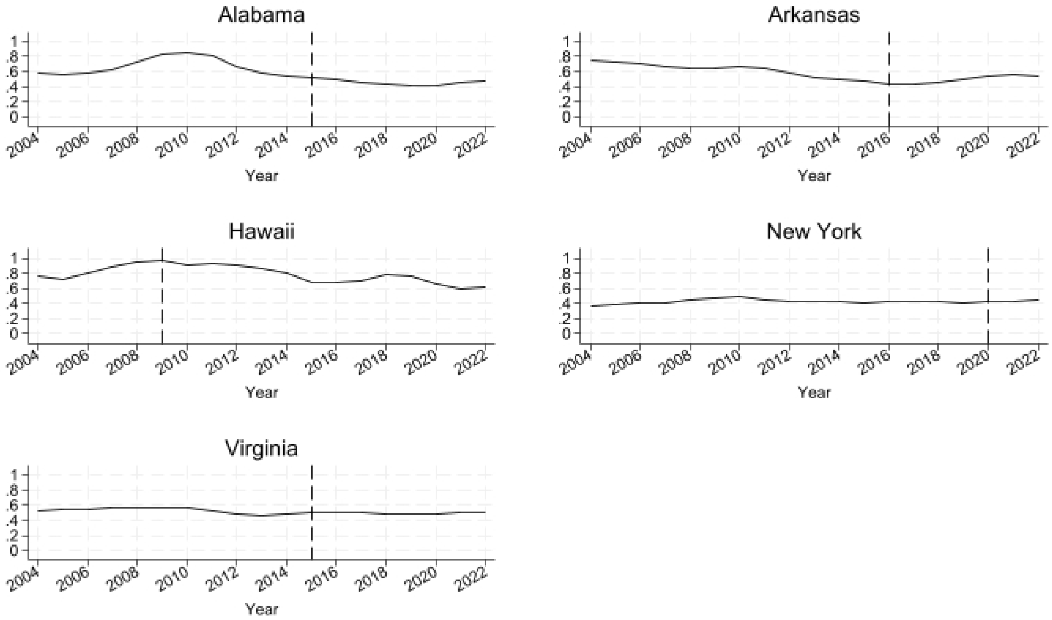
treatment and control groups is not statistically different than zero, and is numerically close to zero, consistent with common pre-trends.

We next address the possibility that our results are driven by some sort of reform endogeneity. The concern is that a change in a population's preferences towards publicity rights and copyrights could drive the decision to enact postmortem publicity rights and also reduce, for example, copyright reliance. In this scenario, the change would be due the underlying preference shift and not necessarily the policy change. To test for this possibility we first examine employment in relevant occupations within each state over time.

If this sort of endogeneity were driving our results we would expect the number of people working in publicity rights reliant occupations to increase relative to the number of people working in copyright reliant occupations in the period leading up to the reform. Figure A.21 shows that ratio over time by state, along with markers for when policy changes occurred (vertical dashed lines). An upward trend in the line prior to policy changes and continuing after policy changes would be consistent with reform endogeneity. This is very clearly not the case for New York or Virginia (the two most populous states in the sample), nor is it the case for Arkansas or Alabama. Hawaii is the only state in the sample that could be consistent with reform endogeneity given the slight upward trend in publicity right reliant occupations prior to the policy change. However, considering the relatively small number of celebrities who fall under Hawaii's publicity rights laws, it seems unlikely that some sort of reform endogeneity could be driving our results.

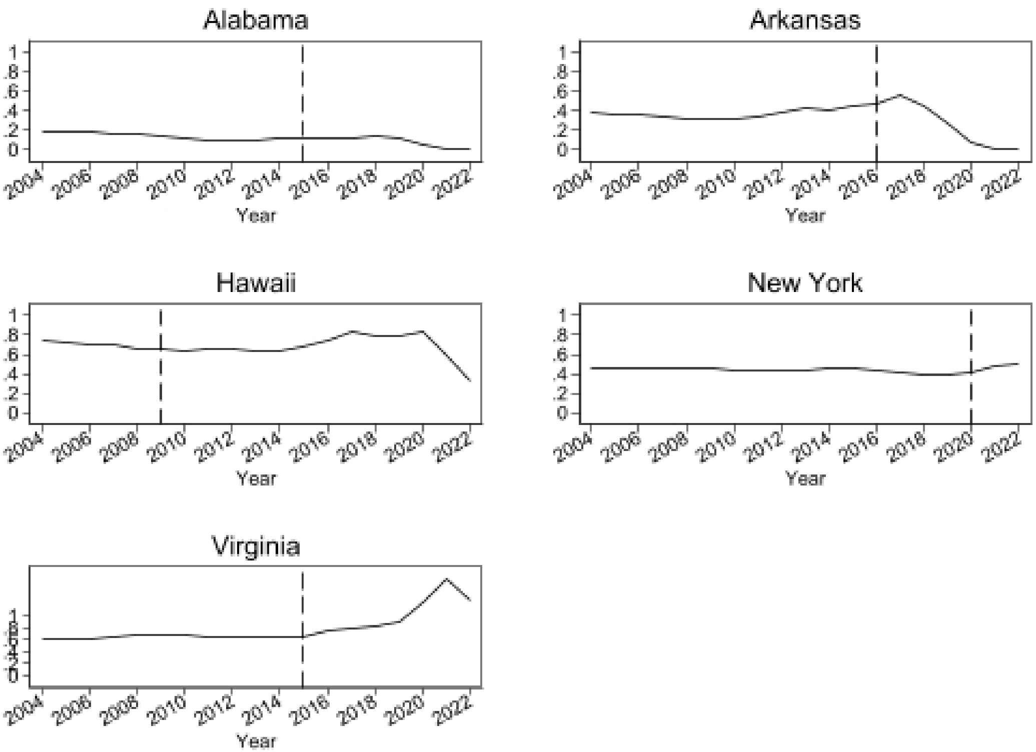
We perform a similar exercise examining the celebrities in our main data set who live in each state. We code them, based on the type of celebrity they are, as being either primarily publicity rights reliant or copyright reliant and calculate the ratio of the former to the latter. Again, if the reduced copyright activity post reform were due to some endogenous factor we would expect this ratio to increase prior to the reform. Aside from Arkansas, which accounts for only 2% of the celebrities in our sample, this is not the case. In all other states the ratio is either flat or decreasing in the time leading up to a state's policy change. These results are also inconsistent with reform endogeneity.

Figure A.20: Ratio of Pub. Rights Occupations to Copyright Occupations by State



Notes: The graphs depict the ratio of state residents who work in occupations that are predominantly publicity rights reliant to those in occupations that are predominantly copyright reliant. Values represent a three-year moving average. Dashed vertical lines represent the date of the state's policy change with respect to postmortem publicity rights. Occupations data is take from the U.S. Bureau of Labor Statistics' (BLS) Occupational Employment and Wage Statistics data series. Using BLS' Standard Occupational Classification System (SOC), we code each occupation within the "Arts, design, entertainment, sports, and media occupations" category (SOC 27) as being mainly copyright reliant, mainly publicity rights reliant, or "not applicable". We sum employment within publicity rights reliant occupations and copyright reliant occupations respectively by state and year, then divide the former by the latter. Occupations identified as copyright reliant include, Art directors, Artists and related workers, Craft artists, Editors, Fine artists, including painters, sculptors, and illustrators, Graphic designers, Music directors and composers, Musicians and singers, Producers and directors, Special effects artists and animators, Technical writers, Writers and authors, News analysts, reporters, and journalists, and Photographers. Occupations identified as publicity rights reliant include Actors, Athletes and sports competitors, Choreographers, Dancers, Entertainers and performers, sports and related workers, Fashion designers, Broadcast announcers and radio disc jockeys, Public relations specialists.

Figure A.21: Ratio of Pub. Rights Occupations to Copyright Occupations by State



Notes: The graphs depict the ratio of state celebrities in our data set who work in occupations that are predominantly publicity rights reliant to those in occupations that are predominantly copyright reliant. Values represent a three-year moving average. Dashed vertical lines represent the date of the state's policy change with respect to postmortem publicity rights. We sum the number of celebrities within publicity rights reliant occupations and copyright reliant occupations respectively by state and year, then divide the former by the latter. Occupations identified as copyright reliant include, actors, architects, artists, film and television producers, media producer, musicians, and writers. Occupations identified as publicity rights reliant include actors, comic, performer, professional athletes, radio personalities, media personality, and fashion designers.