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Using computer vision to measure design similarity: An application to design rights

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A R T I C L E I N F O

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A B S T R A C T

Competition among firms has increasingly been through design. We show how computer vision algorithms can be leveraged to measure the visual similarity of design rights across large data sets of product design images. In particular: we extract and standardize 716,168 unique design images included in US design patents (1976–2023); adapt the structural similarity index measure to quantify design similarities between images; and rigorously validate the resulting measure of design rights similarity. We then use that measure to produce novel empirical evidence that a design space's similarity density exhibits an inverted U-shape with respect to the likelihood of that space's design rights being litigated—a relationship proposed previously but never tested. Our design rights similarity measure should facilitate the exploration of new research questions in the fields of design rights, innovation, and strategy. We grant open access to our code and data resources to encourage research in such fields.

1. Introduction

Firms today have become ever more reliant on design to differentiate themselves (Bu et al., 2022; Ching et al., 2024), to signal a product's features or "credentials" (Ghisetti et al., 2021), to guide consumers' use of novel products (Mugge and Dahl, 2013; Mulder-Nijkamp, 2020), or to create a sense of familiarity (Landwehr et al., 2011). As a result, most such designs are protected through design rights, which reflect firms' appropriation strategies and their investment of considerable resources in securing that protection (Filitz et al., 2015). The key strategic role of design protection is evidenced by the increasing number of design right applications—which totaled some 1.5 million in 2021 alone (World Intellectual Property Organization, 2022)—and the great extent of litigation concerning these rights (Schwartz and Giroud, 2020).

Yet with just a few notable exceptions (viz., Filippetti and D'Ippolito, 2017; Filitz et al., 2015; Heikkilä and Peltoniemi, 2019), research on design rights is rare. So even though design rights (which protect a product's visual appearance) are often viewed as an equal "twin sister" to patent rights (which protect the product's technology or function) (Ikeuchi and Motohashi, 2022; Musker, 2023), our understanding of how design rights affect innovation, strategy, and competitiveness lags far behind our knowledge about the implications of patent rights (Blind et al., 2022; Büttner et al., 2022; Cappelli et al., 2023; Colombo et al., 2023; Dosi et al., 2015; Gambardella, 2023; Kim et al., 2016; Maskus et al., 2019; Van Roy et al., 2018).

This gap in our knowledge of design rights versus patent rights has been exacerbated by recent advances in computer-assisted textual analysis, which have enabled scholars to dig deep into patent rights databases to automate the creation of similarity measures for protected technologies across multiple legal documents (Arts et al., 2021; Bryan et al., 2020; Higham et al., 2021; Magerman et al., 2010). Such automation has augmented researchers' capacity to conduct large-scale empirical studies of how patenting, litigation, and appropriation strategies vary across firms and industries (Arts et al., 2018, 2021). The same cannot be said of design rights, since many important insights into the nature of design protection and its implications—for innovation, strategy, and competitiveness—are based on qualitative evidence derived from small data sets (e.g., Filippetti and D'Ippolito, 2017; Filitz et al., 2015; Heikkilä and Peltoniemi, 2019).

In contrast to patent rights, where an invention is legally protected by means of textual descriptions, design rights are protected only by images (Ghisetti et al., 2021). The claim to a design derives exclusively

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from its visual appearance, as documented in images such as drawings. However, processing images is far more demanding than processing text. It follows that analyzing the similarity of design rights will be a greater challenge than in the case of patent rights. Because of this complexity, prior management research that measures visual similarity via large-scale automated image processing (e.g., Banerjee et al., 2023; Gross, 2020; Jiang et al., 2022) have pursued different computer vision (CV) algorithms to measure similarity but without validating them. Yet such validation is necessary for obtaining reliable empirical results. In short: we do not believe that there currently exist any large-scale, reliable measures of design rights similarity.

Toward the end of filling this research gap, we first devise a way of using computer vision to automate the process of generating a design rights similarity measure from images of documented design rights. This measure enables us (and the community of strategy scholars) to extract management insights from design rights databases, catching up with recent advances in the automation of patent rights text analysis. After comparing different classes of CV approaches (see Online Appendix A), we build a design rights similarity measure based on the structural similarity index measure (SSIM) of Wang et al. (2004). We remark that our measure is especially well suited to determining the similarity (or dissimilarity) of design rights images; since the means of measuring similarity is transparent, we can tailor the approach to not only capture differences in an image's "overall visual appearance" (a vital component of design rights), but also differences in surface shading or line styles, which are of particular importance in design right drawings (USPTO, 2006).

Next, we apply an adaptation of this measure to design rights granted by the US Patent and Trademark Office (USPTO) and conduct three validation tests to ensure that the adapted measure is reliable and accurately assesses the visual similarity between design rights. Initial testing reveals that our similarity measure exhibits theoretically correct correlations with other variables. More specifically, we find a positive correlation between greater similarity and the likelihood that (i) the design originates from the same firm(s), (ii) the design is the work of the same designer(s); and (iii) a citation link exists between them (Arts et al., 2018; Chatman and Jehn, 1994; Gouvard et al., 2023; Haans, 2019). According to our second test, designs that "stand out" from others within the same product category are more likely to win design awards (Bu et al., 2022; Haans, 2019). In particular, we show that firms with original designs—in other words, designs relatively dissimilar to their nearest neighbors (or the most similar "prior art", in the parlance of patent law)—are more likely to receive the prestigious "iF Design Award". The third test establishes that our design rights similarity measure correlates well with the human perception of visual similarity (Chan et al., 2018). We assessed this correlation by recruiting online observers to rate visual similarity across design pairs. We find that our design rights similarity measure is positively correlated with how online observers perceive similarity between designs.

We then employ this validated measure to enhance our comprehension of how firms utilize litigation as an appropriation strategy for their design innovations. In particular, we theorize about how the enforcement of design rights can be shaped by the industry's design context—that is, by the extent to which designs in that space are similar to each other, a notion we label *design space similarity density* (DSSD). Thus our work builds on and provides empirical support for the claim of Filitz et al. (2015), who were among the earliest to address appropriation strategies for design rights, that the relationship between DSSD and litigation is curvilinear and so it is *not* the case, as one might reasonably expect, that a design space with higher DSSD (i.e., populated by designs that are relatively more similar) would be characterized by more litigation. Our empirical analysis reveals that the relationship between DSSD and litigation indeed exhibits an inverted U-shape.

This study makes two main contributions. First, by providing empirical support for Filitz et al.'s (2015) proposition, we contribute to the nascent literature on design rights and their role in innovation, strategy, and competitiveness (see also Filippetti and D'Ippolito, 2017; Heikkilä and Peltoniemi, 2019; Schartinger, 2023). The concept of DSSD is especially useful for elucidating the contextual parameters that inform a firm's decision to initiate litigation. Thus we add to the extant body of research on appropriation strategies by offering an expanded perspective on the heterogeneity of litigation strategies as a mechanism for appropriating value (Reitzig and Puranam, 2009; Reitzig and Wagner, 2010).

Second, and perhaps more importantly, we validate a robust computer vision algorithm for measuring similarity among design rights. Similarity measures are central to many management and strategy analyses of intellectual property, especially those that focus on firms' strategies for filing, litigation, and appropriation (Alcácer and Gittelman, 2006; Almeida and Kogut, 1999; Arts et al., 2018; Heikkilä and Peltoniemi, 2019; Jaffe et al., 1993; Makri et al., 2010; Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011; Thompson, 2006). In support of these efforts, Whalen et al. (2020) have conducted large-scale text analyses of patent rights and have generously shared their data. There is, unfortunately, neither an equivalent similarity measure nor a database of design rights. We address this gap by providing a validated design rights similarity measure and by offering full access to our code and data. To support further research, we also give an easy-to-follow description of our measure. We hope thereby to stimulate research on design rights—much as how the introduction of text-based similarity measures (e.g., Arts et al., 2018, 2021) stimulated research on patent rights.

The rest of this paper proceeds as follows. Section 2 presents our main arguments, which posit a relationship between DSSD and firms' design rights litigation strategies. In Section 3 we develop a new measure of design rights similarity and also document a series of validation tests. We are then in a position to analyze and present the results of the relationship between DSSD and litigation, which is the focus of Section 4. We conclude in Section 5 with a discussion of the potential applications of our data, methods, and similarity measure.

2. Design rights, design space similarity density, and litigation strategies

Design rights are the chief legal means of safeguarding the visual appearance of products, thereby granting firms temporal protection for their design innovations. Because the legal protection of product designs is inherently different from that of technological inventions, we shall commence by defining design rights (Section 2.1). We then show how design rights filing strategies reflect the similarity between designs in a design space (Section 2.2). Finally, we discuss Filitz et al.'s (2015) central proposition, whereby the enforcement and litigation of design rights are driven by the extent of similarity across designs in a given design space (Section 2.3).

2.1. What are design rights?

Design rights protect the visual appearance (or aesthetic features) of a product. A key requirement to be eligible for protection is that the design must be new and not previously disclosed to the public. Design rights are known as design patents in the United States (USPTO, 2006) and called registered community designs (RCDs) in the European Union

(EU) (Schartinger, 2023).[1] A design right in the US is granted only after an examination process; in practice, however, design right applications are presumed valid unless proven otherwise. Hence the likelihood of obtaining a design right is high when the application is filed properly, which renders the US regime similar in effect to the EU regime (where rights are registered without substantive examination). Online Appendix B reviews both intellectual property regimes for design rights.

Designers (usually the firm as the potential assignee) file their applications for design rights in the proper jurisdiction: either the USPTO or the EUIPO (European Union Intellectual Property Office). In either case, the protection is limited to the product's visual appearance. The scope of design rights is therefore protected by means of images—usually in the form of so-called wireframe drawings though occasionally by way of photographs or computer-generated images. Of particular significance in design rights drawings are the use of specific line styles—that is, solid versus broken lines—as designers claim only the portion of the design that is drawn in solid lines, and the use of surface shading, which is used to show the contours of surfaces (USPTO, 2006).[2]

Thus, because design rights protect a different aspect of the product (its visual appearance) compared to patent rights (its technology and function), they differ in how they are safeguarded: while patent rights are protected through textual descriptions—namely, the written claims made in the patent application and its abstract—design rights are secured based only on the design's visual appearance. That visual appearance is represented by an image, which corresponds to the design right's legal claim (which means that there is only one claim). Hence, what is needed to evaluate similarity between design rights is a comparison between images rather than one between texts.

2.2. Inter-industry variations in motives to file and in design space similarity density

Scholars have observed substantial variation in the scope of design rights protection based on the design space to which the focal product belongs—for example, machinery, shoes, or mobile phones (Heikkilä and Peltoniemi, 2019; Saidman, 2008). When a design space features low similarity among designs, design rights offer a broad protective scope in recognition of the extensive differentiation within the design space. Conversely, the scope of protection in design spaces characterized by high similarity is narrower and often limited to preventing exact duplications (Filitz et al., 2015; Heikkilä and Peltoniemi, 2019; Lemley, 2013). In what follows, we elaborate on why filing behavior differs across industries and on how these differences give rise to observed inter-industry variations in DSSD.

In shedding light on the antecedents of differences in filing strategies (i.e., limited vs. extensive), prior research has identified product and industry parameters that shape firms' decisions about whether or not to file (Heikkilä and Peltoniemi, 2019; Schartinger, 2023). In their qualitative study of design rights strategies across firms in various German industries, Filitz et al. (2015) give machinery, automotive, electronics, and tool designs as prime examples of industries that use selective, "judicious" approaches; however, firms in the shoe industry tend to employ more pro-active "all you can file" strategies.

Theoretical insights suggest that these inter-industry differences arise from industry-specific cost structures. Beyond the direct costs of securing design rights,[3] indirect costs—for instance, those due to forfeiting alternative protection strategies (e.g., secrecy) or first-mover advantages—are likely to exhibit pronounced inter-industry variations (Cohen et al., 2000). These indirect costs are especially crucial for products like machinery, whose design is tightly linked to function and so disclosure risks exposing internal mechanisms (Filitz et al., 2015). For example, a producer of agricultural machinery might apply for a design of a tractor hood that includes specific vent patterns or contours that are visually distinctive yet also serve to optimize engine ventilation, prevent overheating, and/or improve aerodynamics. Or a producer of construction machinery might design a uniquely curved boom to provide better reach or allow the excavator to work in confined spaces while maintaining structural integrity under heavy loads. In both examples, the design rights could reveal insights about the engineering choices that inform the design (e.g., material strength, load distribution, stress points) and thus enable "reverse engineering" by competitors. Supporting this view, Ikeuchi and Motohashi (2022) note that protecting highly integrated designs may inadvertently reveal underlying technological innovations.

Thus industries such as machinery, automotives, electronic, and tools face high indirect costs of filing design rights. These high costs naturally deter filing and so firms in these industries tend to file less; hence the respective design spaces in which these firms operate have a low similarity density: designs in the space have lower degree of similarity to each other (i.e., there is low DSSD). Yet the lower similarity density does yield some benefits. In particular, design rights in low-DSSD contexts have broader (and, as will be explained in Section 2.3, also clearer) scope—allowing firms to engage in valuable uses of these rights through cross-licensing and contract manufacturing (Heikkilä and Peltoniemi, 2019).

In contrast, there are minimal indirect costs for industries, such as shoe manufacturing, where design is less tied to function. Firms in these industries therefore adopt all-you-can-file strategies because the risks associated with disclosure are negligible (Filitz et al., 2015). In such industries, the low indirect costs encourage filing and so firms tend to file more. In turn, the high volumes of design rights filings result in a design space with many similar designs, or a high-DSSD context (Schartinger, 2023). Although the indirect costs of filing are low in these industries, the high degree of similarity between design rights constricts the scope of design protection—to the extent that design rights in such industries serve primarily to prevent exact imitation (Heikkilä and Peltoniemi, 2019). Nonetheless, firms must remain active in filing design rights in order to defend their freedom to operate (Heikkilä and Peltoniemi, 2019).

In sum, inter-industry differences in indirect costs lead to distinct design rights filing patterns. When the indirect costs of obtaining design rights is high, firms can be expected to exert discretion in choosing

[1] In the United States, "patent" is used more generally to cover both the protection granted to a product's visual appearance, or the product's (or process') technology or function. Thus the USPTO distinguishes between "design patents" and "utility patents". In the EU, design rights are known as RCDs whereas patent rights refer only to the rights protecting a product's technology of function. We use in this paper the terms "design rights" and "patent rights", the former applying to a product's visual appearance; the latter to a product's technology or function (Filitz et al., 2015; Harhoff et al., 2003; Hegde and Luo, 2018).

[2] Given these aspects of design rights images, any image comparison approach must be able to judge that (a) two designs are *similar* when they are indeed similar except for formatting (as when one is a wireframe drawing and the other is a photograph or computer-rendered image); and (b) two designs are *different* when they have a similar structure, but they have differences in either line styles (e.g., only one of them is covered with many broken lines) or surface shading (e.g., only one of them uses extensive shading). Such correct comparisons are enabled by the adaptations discussed in Section 3.2.

[3] Firms can reduce the per-unit direct costs associated with securing design rights by accumulating experience in filing for them (Reitzig and Puranam, 2009; Reitzig and Wagner, 2010) or by hiring or developing legal expertise (Foster, 1986; Somaya, 2012). Such strategies are not limited to specific industries—which may partly explain the robustness of our insights to the inclusion, as controls, of (i) aggregate industry-level design rights filings, (ii) intra-industry variations across firms in design rights filings, and (iii) aggregate industry-level number of attorneys (see Sections 4.2 and 4.3). It follows that inter-industry variation in direct costs is not a significant driver of our results.

which products they wish to protect—a strategy whose effect is to expand the scope of legal protection (a low-DSSD context). But when the indirect costs of obtaining design rights is low, firms are more likely to file a multitude of design rights to cover the various design iterations of their products. This strategy produces a design space in which many similar designs co-exist and (because of their strongly similar appearances) are protected only within their narrowly defined scopes (a high-DSSD context) (Schartinger, 2023).

2.3. Inter-industry variations in design space similarity density, scope uncertainty, and litigation

Having explained the existence of inter-industry differences in filing intensities, which lead to different DSSDs, we are now in a position to discuss why the DSSD has implications not only for a design right's scope of protection but also for the *level of uncertainty* about that scope. Furthermore, the level of uncertainty surrounding the scope of design rights bears major implications for whether firms use litigation to appropriate value from those rights.

Litigation can add to a firm's inimitable resources and so is an important mechanism for appropriating value (Reitzig and Puranam, 2009; Reitzig and Wagner, 2010). However, litigation strategies are both costly and risky (Lanjouw and Schankerman, 2001). Instead of litigation, firms can pursue less risky ways of enforcing their rights—for instance, privately negotiating an informal settlement.

Theories on litigation call for its strategic use only when there is considerable uncertainty or conflicting beliefs about the scope of applicable design rights (Bebchuk, 1984; Priest and Klein, 1984; Somaya, 2003; Waldfogel, 1998). Bringing a case to court through litigation (i.e., formal enforcement)—rather than seeking an alternative solution (i.e., informal settlement)—suggests that plaintiff and defendant each believe they have a reasonable chance of winning the case and thereby formally enforcing their rights. Hence firms will go to court only if the scope of protection is highly uncertain[4]; when that scope is relatively certain, firms are less inclined to litigate.

It is interesting that, unlike the monotonic relationship between DSSD and scope of protection (since higher DSSD results in narrower scope), the relationship between DSSD and uncertainty in the scope of protection is theorized to be an inverted U-shape (Filitz et al., 2015). In other words, uncertainty about scope is low whenever DSSD is either very low or very high; in either of these extreme cases, firms seldom litigate to settle disputes over design rights. Meanwhile, at moderate levels of DSSD, uncertainty about scope is high and so firms rely more on courts and litigation to enforce their rights (see also Heikkilä and Peltoniemi, 2019).

Consider first the case of a low-DSSD context, where the scope of design rights is made clear through the up-front effort of industrial participants carefully checking their work before filing. Filitz et al. (2015) qualitatively document how these firms make sure, *before* filing, that their designs clearly differ from prior art; the implication is that firms not only check their own previous designs but also extensively search all prior art. There are two incentives for such a thorough review: (i) in terms of costs, the sparsity of relevant design rights in low-DSSD contexts makes such reviewing less costly; and (ii) in terms of benefits, such due diligence allows firms to be "confident about the validity and scope of protection of their own [rights], and the validity of rivals' [rights]" (Filitz et al., 2015, p. 1201)—and such clear rights facilitate firms' extraction of value from their design rights transactions, such as cross-licensing and contract manufacturing (Heikkilä and Peltoniemi, 2019). Hence the uncertainty about the scope of protection is relatively low, which means that firms are less reliant on litigation as a rights enforcement strategy.

Now consider the case of a high-DSSD context. Here the design space is dense with many similar designs. That density accounts for a steep increase in the costs of pre-litigation research, since identifying all prior art becomes an especially arduous and expensive task. This difficulty arises from the multitude of existing design rights, many of which are very similar to one another, that clouds the distinction between new and prior designs.[5] As a consequence, firms in this design space are typically less inclined to search the prior art before filing for design rights. Yet the rampant filing of designs has the further effect of creating a common expectation that a design right's scope of protection is narrow—and since design rights can thus protect only against exact copying, the level of uncertainty regarding their scope is correspondingly low. In these cases, the clear-cut nature of the rights protection's scope implies that any disagreements can easily be resolved prior to reaching the litigation stage.

The same cannot be said for contexts characterized by moderate DSSD; here, firms are uncertain about the scope of their protection and are therefore motivated to file design rights in order to block other firms. On the one hand, such a design space is (unlike the machinery space) heavily populated with designs and so "careful homework" is quite costly; on the other hand, the scope to the "nearest" competitor is (unlike for shoes) "somewhat" distant and therefore unclear. In line with these ideas, Heikkilä and Peltoniemi (2019) report how firms in the sauna heater industry engaged the courts mostly in the middle phases of that industry's evolution toward higher DSSD.

Thus we can see how the DSSD context shapes the degree of uncertainty about the exact scope of protection, with low levels of uncertainty at each end of the spectrum but with a high level of uncertainty in between. We therefore expect low levels of litigation at both ends of the similarity density spectrum, where firms avoid costly litigation battles to resolve ownership because the scope of protection is already clear. Hence we presume that only at moderate levels of similarity density in a design space will industry participants have appreciable uncertainty about the scope of design rights and that these rights cannot be easily enforced through other means. It is therefore in this "middle" region that we expect most litigation to occur. All these considerations lead us to posit that the relation between DSSD and litigation will be represented by an inverted–U-shaped curve.

3. Deriving a similarity measure: data, methods, and validation

The core of our argument is that similarity matters because similarity density in design spaces shapes a firm's strategies for appropriation and litigation. However, an empirical test of this hypothesis requires a *design rights similarity measure* that is both accurate and easily applied to a large corpus of design images. However, operationalizing such a measure presents a challenge from the methodological standpoint (Bu et al., 2022; Ching et al., 2024; Mugge and Dahl, 2013; Mulder-Nijkamp, 2020). Our aim is to devise a measure based on the direct comparison of images that can be automated on a large scale, unlike the undeniably

[4] This prediction is confirmed by an interviewed design rights lawyer, who stated: "Infringement cases tend to be close calls. Because people feel like 'I've got a chance that I can win this.'"

[5] Readers should bear in mind that the term "density" (which describes how much the designs in a design space resemble each other) differs conceptually from the term "thicket". Patent thickets "consist of patents that protect components of a modular and complex technology" (Hall et al., 2013, p. 2). Because they depend crucially on the modularity of the underlying technology, patent thickets amount to a unique patent rights phenomenon. Designs, however, cannot be modular because a right is granted for the "overall appearance" (USPTO, 2006, p. 29) of a single product design. The distinction is clear when we think of patent thickets as compounding the problem of density: commercializing a modular product requires that the firm evaluate intellectual property claims for hundreds of components (the thicket), each of which may be in a high-density design or technology space (the idea of density can be transplanted to technology to describe how much patents in a technology space resemble each other).

accurate yet hard-to-scale approach of conducting surveys (Mugge and Dahl, 2013; Mulder-Nijkamp, 2020), or approaches custom-designed to evaluate specific products (see Landwehr et al., 2013; Liu et al., 2017). We introduce a novel measure for assessing the visual similarity of designs by adapting Wang et al.'s (2004) structural similarity index measure (SSIM). We shall start by presenting our data, which consists of USPTO design rights images (Section 3.1). Next, we explain the essential step of standardizing images (Section 3.2) before illustrating why SSIM is well suited for adaptation as a similarity measure for design rights (Section 3.3). We then employ three different strategies, based on empirically established relationships, to validate our adapted similarity measure (Section 3.4).

3.1. Image data and design rights

The USPTO has archived all previously granted design rights in an open-access database (available at https://data.uspto.gov/bulkdata/datasets). Because images represent the fundamental aspect of what is being protected, this database contains images from all granted design rights—images that researchers can analyze when evaluating the visual similarity of granted designs (see Online Appendix Fig. E.1 for a sample US design patent and the information it contains). The database includes a wide range of bibliometric information: the name(s) of the designer(s), the assignee(s) and their geographic location(s), and references.

We collected all design rights granted during the 1976–2023 period from the USPTO Bulk Data Storage System, which included 716,168 unique product design images. More than 98 % of these images are wireframe drawings; the rest are either photographs or computer-generated images. Yet because these design images are embedded in design rights documents that also contain text, researchers must undertake “data cleaning”—here, image pre-processing—in order to standardize the images.

3.2. Preparing the design right data: standardizing images via pre-processing

The aim of pre-processing is to ensure that the images are comparable enough that the computer algorithm does *not* pronounce a pair of images to be different when they are actually similar (or vice versa). Toward that end, standardizing image data proceeds in three steps. We illustrate those steps in Fig. 1, using mobile phone designs as an example.

First, design rights images have a noisy background. Thus the front-page image of a design rights document contains, besides the object of interest (the product design's image), much textual information about the creation of that product's design. For an enlarged view of such text, see Online Appendix Fig. E.1. To isolate the focal image, the first pre-processing step removes all irrelevant elements by “cropping in” the object (Fig. 1's “Step 1: Fix noisy background”).

Second, images may have spatial alignment issues even after cropping. A frequent source of spatial misalignment is differences in orientation (e.g., the object is standing upright in one image but is rotated 90° in the comparison image). So in Step 2, spatial alignment differences are fixed by, inter alia, ensuring that images in the same design subclass (e.g., agricultural and construction machineries, shoe soles, mobile phones) have the same orientation (i.e., all “portrait” or all “landscape” orientation).

Third, not all images are in the same size: the width and/or length may differ between images being compared. Hence Step 3, “Fix size difference” in Fig. 1, standardizes all images in the same design subclass by padding them with white boundaries to match the maximum dimensions found within the subclass. After this padding, each image is resized so that its longer side measures 256 pixels, thus ensuring uniformity across all images.[6]

These three pre-processing steps are applied to all images in our data set for the purpose of minimizing the likelihood of computer vision algorithms declaring that similar product design images are different. Pre-processing does require understanding and adapting to the context, but the resulting noise removal leads to a more accurate assessment of similarity. If one compares, for instance, images of the two mobile phones before and after pre-processing (Fig. 1), then there is no question that recognizing similarities between the two mobile phones is much easier once the images have been pre-processed.

Finally, for the small subset of photographs and computer-generated images we use edge detection (Canny, 1986) to convert them to wireframes.[7] Together with the three main steps, this last component of pre-processing ensures that the accuracy of our similarity measurements are not compromised by formatting differences.

3.3. Understanding and adapting the structural similarity index measure for design rights

The SSIM (Wang et al., 2004) is one of the most popular means of assessing the similarity of two images. Here we wish to offer the reader some intuition about how this measure imitates human perception and to explain how its implementation can be adapted to a specific research context. See Online Appendix A, which includes a systematic comparison of alternative CV algorithms along with our detailed reasoning for why this measure is the most suitable one for assessing similarity between images of design rights.

Consider first how visual perception works in humans. We view an image by its three interrelated aspects of brightness, contrast, and structure (Oliva and Torralba, 2006; Rogowitz et al., 1998; Wang et al., 2004). Fig. 2 illustrates these factors of human visual perception by comparing constructed images that exhibit variations along those aspects as compared with a baseline image of a mobile phone that is uniformly gray. In Fig. 2(a), the image's brightness has been increased so that the phone appears as uniformly white. Fig. 2(b) is the same image after being altered to show increased contrast—so instead of being uniformly gray or white (as in the previous two images), the surface now appears with a marbled pattern. Finally, Fig. 2(c) exemplifies alteration of the phone by changing its structure.

The SSIM constructs similarity scores (that range from 0 to 1) between a pair of images by comparing their brightness, contrast, and structure; these scores are then multiplied together to yield an overall measure of similarity. For the phones in parts (a)–(c) of Fig. 2, the variations are reflected in the similarity metrics derived from this measure; see the last column in Table 1.

Our analysis begins with the baseline mobile phone design shown in Fig. 2. When this design is compared with itself, the similarity is perfect (of course) and so yields a similarity score of 1.000. If we now compare the baseline design with a version that features increased brightness, as in Fig. 2(a), then the brightness similarity score drops to 0.914. This result indicates that enhancing the brightness makes the design less similar to the baseline.

Next we look at Fig. 2(b), in which a marbled pattern has been added to the phone's design. This addition creates more variation in the image's

[6] This reduction is unnecessary if the data set is small and if computing capacity is not a constraint. In our case, the reduction did not visibly distort the design but did significantly improve computing speed.

[7] In computer vision, edge detection is fundamental to recognizing objects; Canny's approach and its variants are still state-of-the-art. We use a variation that includes Gaussian blurring, which smooths out the subtler lines, to obtain even greater accuracy.

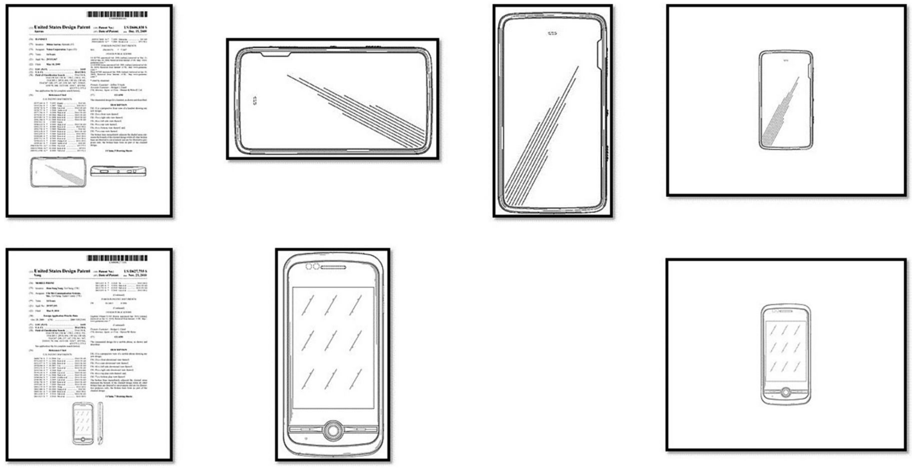

Fig. 1. Design rights pre-processing steps: illustration using mobile phone designs.

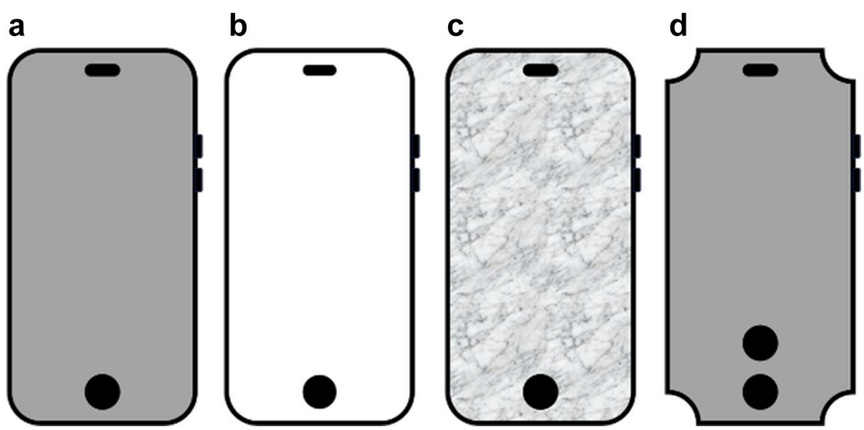

Fig. 2. Visual aspects of an image.

Table 1
Structural similarity index measure: aspects and design similarity.

Baseline phone design as compared with	Brightness	Contrast	Structure	SSIM
Itself	1.000	1.000	1.000	1.000
Variation in Brightness	0.914	0.961	0.999	0.876
Variation in Contrast	0.917	0.955	0.993	0.870
Variation in Structure	0.991	0.982	0.557	0.542

Notes: Following Wang et al. (2004), we calculated the aspect-specific (i.e., brightness, contrast, structure) similarity as defined by Eqs. C.2, C.3, and C.4 (respectively) in Online Appendix C.

pixel intensities than in the baseline design, so its similarity in terms of contrast drops to 0.955. We infer from this result that the marbled pattern renders the phone's design noticeably different in terms of contrast.[8]

Fig. 2(c) shows a variation in the structure of the phone design. Here we see that, although the altered image exhibits greater similarities—than do Fig. 2(a) and (b)—to the baseline in terms of brightness and contrast, its similarity to the baseline with regard to structure is low (at 0.557).

As mentioned previously, the final SSIM score is a product of the similarities in the three distinct aspects. Once again, comparing the baseline mobile phone design with itself yields perfect similarity and thus a similarity score of 1.000. If we compare the baseline design with the other designs—in Fig. 2(a), (b), and (c)—then the SSIM returns scores that are less than 1.000, indicating various degrees of similarity differences. It is worth noting that a change in *any* of the three aspects (brightness, contrast, structure) will affect the SSIM score. Hence we can reasonably conclude that SSIM is sensitive enough to detect differences along any of the major aspects that matter for visual perception.

Parts (a)–(c) of Fig. 2 illustrate the manipulation of images in each aspect of visual perception (without perturbing the other aspects too much). All three of these aspects clearly matter to the human perception of images and are closely interrelated. It is for this reason that, in seeking to capture humans' visual perception, the SSIM algorithm evaluates all three of these visual aspects and then multiplies them together. Observe that these aspects correspond to simple statistical characteristics of the distribution of pixel intensities of images: brightness corresponds to the image's *mean* pixel intensity, contrast to its *standard deviation* of pixel intensity, and structure to the *covariance* between pixel intensities of the images being compared. For a mathematical yet approachable account of the SSIM, see Online Appendix C.

Building on this foundation, we adapted the Wang et al. (2004) measure to analyze pairs of (pre-processed) design rights images using

[8] As brightness, contrast and structure are interrelated, changes in the brightness of an image, for example, often result in changes in contrast (and vice versa). The increased brightness of Fig. 2(a) also increased the image's contrast, since the button and outline remain black and so are now in starker contrast with the body. Our changes in Fig. 2(b) similarly increased the image's contrast while reducing its brightness.

Python's opencv and scikit-image library.[9] Our implementation maximizes one of Wang et al.'s "window size" parameters so that the algorithm measures similarity based on the "overall visual impression" of a design rights image—which is exactly what design rights examiners evaluate as being similar (or not) to prior art. In addition, we account for similarities in all three aspects—brightness, contrast, and structure. The reason is that structure decisively alters a design's "overall appearance" (USPTO, 2006, p. 29) while brightness and contrast are useful to "show clearly the character and contour of all surfaces" (USPTO, 2006, p. 8) of three-dimensional product designs. Indeed, as we show in Online Appendix Fig. E.3, the SSIM score is also sensitive (through the structure term) to differences in *line styles* (that is, solid versus broken lines), which take on particular significance in design rights drawings. Because broken lines indicate design areas over which the designers do *not* claim ownership, two designs that are similar except for their line styles should be considered, and measured, as visually different because they protect different parts of a design. Our parametric choices are therefore an accurate reflection of this particular context. Interested readers may refer to Online Appendix D for a discussion of the parameters that researchers can fine-tune to accommodate other conditions (as when, e.g., an implementation requires that the product's structure be emphasized more than its brightness or contrast).

3.4. Validating the design right measure

In performing three validation tests to ensure that our design rights similarity measure correctly identifies design similarities, we drew inspiration from the methodologies advanced by Arts et al. (2018), Arts et al. (2021) and Chan et al. (2018). These tests are detailed in what follows.

3.4.1. Correlational validity via bibliometric information in design rights

The first validation test checks for whether our design rights similarity measure exhibits the expected theoretical correlations with existing variables (for an example of this validation strategy used in the context of patent rights, see Arts et al., 2018). More specifically, we would expect designs from the same firm or from the same designer to be more similar (Chatman and Jehn, 1994; Gouvard et al., 2023; Haans, 2019). At the same time, because design citations are generated based on comparisons of visual similarity (USPTO, 2006), we expect those designs whose filings cite each other to be similar.

Leveraging the bibliometric information contained in design rights documents, we first code binary indicators that are set to 1 only in following cases (otherwise, they are set to 0): a pair of design rights applied for by the same firms(s) ("same firm(s)", column [1] in Table 2); a pair of design rights sharing at least one designer ("same designer(s)", column [2]); a design right being cited by its pair ("citation", column [3]). The values reported in this table confirm that our similarity measure exhibits all the expected positive correlations.

Table 2
Design similarity and incidence of same firms, same designers, and citations.

	[1] Same firm(s)	[2] Same designer(s)	[3] Citation
Design similarity	0.116***	0.030***	0.015***
	(0.001)	(0.000)	(0.000)
FE on focal design	Yes	Yes	Yes
R^2	0.312	0.118	0.047

Notes: We first randomly selected 7162 designs (1 % of the total number of unique designs). We then formed a unit of analysis (a design pair) by comparing all other designs within the same subclass against each of these focal designs. This pairwise combination yielded 2,735,426 design pairs. We estimated linear probability models. Standard errors (in parentheses) are clustered at the focal design level. FE = fixed effects.
*** $p < 0.01$.

3.4.2. Predictive validity via design awards

Our second test checks that the proposed measure can be used to predict some future outcomes—in our case, the likelihood of a firm receiving a design award. This approach echoes that of Arts et al. (2021), who use awards (such as winning the Nobel prize) to validate a technological similarity measure. The idea that firms with original designs (i.e., designs with a low degree of similarity to prior designs) are more likely to win design awards has prior theoretical support (Bu et al., 2022; Haans, 2019).

For this test, we make use of the iF Design Award. Established in 1953, it holds the distinction of being one of the world's longest-running and most esteemed design awards (Xia et al., 2016). Because award recipients represent a broad set of industries and product categories, there is considerable overlap with the set of firms and industries included in our design rights data. Moreover, the iF label bestowed upon recipients carries real commercial value—showcasing the exceptional nature of those who are recognized (Hsu et al., 2023).

Thus we first identified all iF Design Awards during the years 1976–2023. Matching design rights directly to awards proved to be a challenge, since design rights do not provide clearly identifiable product names that would make the linking straightforward. However, the iF data do reveal whether a *firm* won award(s) in a particular *year*. We therefore linked design rights to awards, at the firm–year level, by matching firm names mentioned in the awards to design rights assignees (i.e., firms holding the design rights). Our dependent variable is a count of the number of awards a firm receives in a given year.

For the independent variable, we adopted a three-step process for calculating average design (un)originality: (i) identify all designs filed by the firm in the year considered; (ii) for each design in the set, measure its level of (un)originality by averaging its similarity against five of its most similar peers in the same design subclass; (iii) average the measure of (un)originality identified in step (ii) over all the designs identified in step (i).[10] We then aggregated these similarity scores across all focal designs of the firm in that year to determine the average design (un) originality of the firm's produced designs in that particular year. A higher average similarity suggests that the firm's designs tend to be less original; conversely, a lower average is indicative of greater originality and shows that the firm's designs were less similar (to their closest peers in the same design subclass) during the focal year.

We use a Poisson model to predict the number of awards in a firm–year while accounting for firm and year fixed effects and for the number of designs filed by the firm in that year (so as to account for the firm's overall design productivity). Our final data set consists of a panel comprising 794 firm–year observations that span 129 firms. The regression results reported in Table 3 establish that producing designs that are less original is associated with receiving fewer design awards.

3.4.3. Perceptual validity via human validation survey

The last validation test shows that our measure correlates well with how humans assess design similarity (cf. Chan et al., 2018). For this test, we hired (via Amazon's Mechanical Turk) online human observers to assess the similarities between pairs of design. Response quality was ensured in three ways. First, we limited the subject pool by requiring that online observers be located in the United States (and with IP addresses matched to a US location). Second, we required all online observers to score at least 95 % on a human intelligence test. Our third restriction was to implement comprehension checks throughout the

[9] See https://pypi.org/project/opencv-python/ for documentation on opencv; for documentation on scikit-image, see https://pypi.org/project/scikit-image/.

[10] Our insights are robust to using instead either the one or three most similar design(s). These results are not reported here but are available upon request.

Table 3
Average design (un)originality predicts number of design awards.

	Number of design awards
Average design (un)originality	−1.646***
	(0.593)
Number of designs filed	Yes
Firm FE	Yes
Year FE	Yes
N	794
Log–pseudo-likelihood	−605.491

Notes: We estimate employing firm and year fixed effects conditioned out with Poisson pseudo–maximum likelihood models. The firm fixed effects (FE) mean that firms must have won at least one award, over the entire observation period, to be included in the sample. The year fixed effect allows us to control for possible evolution of award criteria over the years. Reported values are estimated coefficients. Standard error (in parentheses) is clustered at the firm level.
*** $p < 0.01$.

survey and then to exclude all survey responses from online observers who failed any of those checks.

These observers were asked to rate visual similarity—between pairs of product design images from granted design rights—on an 11-point Likert-like scale that ranged from 0 ("not similar at all") to 10 ("completely similar"). We randomly sampled product design pairs from three design subclasses: mobile phones, kitchen utensils, and interactive computing[11]; thus we covered a representative range of popular product designs (Online Appendix Fig. E.2 shows an excerpt from the survey). A total of 3216 design-pair similarity ratings from these online observers served as the unit of analysis for validating our measure of design rights similarity.

Table 4 summarizes our regression analysis of SSIM and human assessments of similarity. We find a strong positive relationship between design similarity, as measured by SSIM, and the ratings provided by online observers. Thus, our design rights similarity measure aligns closely with human perceptions of similarity.

4. Results

In Section 2 we hypothesized that litigation rates would exhibit an inverted–U-shaped relationship with respect to the similarity density of the associated design space. This proposition can be tested by linking our design rights similarity measure with a litigation data set. We shall present the data and methods employed (Section 4.1), detail our results (Section 4.2), and describe the robustness checks (Section 4.3).

Table 4
Design similarity measure correlates with human assessment of similarity.

	Human assessment of similarity
Design similarity	1.547***
	(0.260)
Observer FE	Yes
N	3216
Log–pseudo-likelihood	−6608.756

Notes: We estimate an ordered logistic regression model that includes dummy variables for each online observer. Reported values are estimated coefficients. Standard error (in parentheses) is clustered at the online observer level. FE = fixed effects.
*** $p < 0.01$.

4.1. Data and methods

This analysis requires that we operationalize the notion of a *design space*. For that purpose, we use the US Patent Classification (USPC) system at the subclass level. Its 5150 unique design subclasses (e.g., agricultural and construction machineries, shoe soles, mobile phones) correspond to the most granular design classification available.

Our unit of analysis is the subclass–year, which allows us to track the evolution of design spaces. We use a data set comprising 22,550 subclass–year observations; for the period covered by our study, these observations include at least one litigation case for each subclass.[12] Much as with the calculation of design similarity in Section 3.4.2, we measure DSSD (our independent variable) by (i) averaging the design rights similarity measures for a focal design and its five nearest (i.e., most similar) designs in the same subclass and then (ii) aggregating the similarity scores at the subclass–year level.[13] This approach facilitates our exploration of the most relevant and possibly contentious comparisons.

Fig. 3 illustrates the differences in similarity density across design spaces. The graph portrays two design spaces (highlighted by Filitz et al., 2015) with different similarity densities: the design space of shoe soles (USPC D02 959000) and that of agricultural and construction machinery (USPC D15 069000).[14] We observe that the average DSSD of designs for shoe soles is higher than that for agricultural and construction machinery. These results support our argument regarding inter-industry differences in filing (see Section 2.2.) while confirming Filitz et al.'s qualitative study, which documented heterogeneous design rights filing strategies across these subclasses (see Section 2.2). Note especially that both lines in the figure show also that DSSD increases over time—an outcome that conforms with Heikkilä and Peltoniemi's (2019) hypothesis that design rights filing strategies tend to evolve from judicious to indiscriminate. These results in themselves demonstrate the utility of our measure for building evidence concerning theories of innovation, strategy, and competitiveness.[15]

We construct our dependent variable by extracting design right litigation cases from the publicly available USPTO's Patent Litigation Docket Reports Data (Toole et al., 2024). These data include records of all litigation cases (either as plaintiff or defendant) associated with a given design right within any given year in the 2003–2020 span. Thus our dependent variable (*Litigation*) is the total number of litigation cases in a particular design subclass in a particular year.

By controlling for the subclass–year level characteristics, we can isolate the relationship between DSSD and litigation. As discussed in Section 2, design spaces characterized by a high similarity density (i.e., a high degree of similarity between designs) typically contain a large number of designs. So in order to establish that our results are driven by similarity density and not the plentitude of designs, the regressions control for the total number of designs filed within a given subclass–year (*Design Filings*). In addition, we control for the average number of designs filed per firm and for the variance in the number of designs filed across firms (via *Ave. Firm Designs* and Var. *Firm Designs*) to account for

[11] For example, the design subclass of "interactive computing" consists mostly of "graphical user interface" designs. To construct a randomized sample, we randomly picked three designs (D1, D2, and D3) in one of the three design subclasses. This sampling allowed us to create design pairs D1–D2, D1–D3, and D2–D3. The same process was repeated for the other two design subclasses.

[12] There are 52,962 subclass–years altogether. Across our entire observation period, however, most subclasses experience no litigation. Hence the main analysis leverages only those subclasses that exhibit some intra-subclass variations in the dependent variable. Nevertheless, the same insights are delivered by Fig. 4 in Section 4.2 (which plots inter-subclass variations) or by a random-effects model (in which we include all observations; see Section 4.3).

[13] In this context, too (cf. note 10), our insights are robust to using instead either the one or the three designs most similar to the focal design.

[14] The subclass of shoe soles falls under the broader design class for apparel in USPC Class D02, which includes shoes, while the subclass of agricultural and construction machinery belongs to the broader design class for machines in USPC Class D15.

[15] Results from a regression analysis confirm both the distinctiveness of these two design spaces and the presence of a common upward trend.

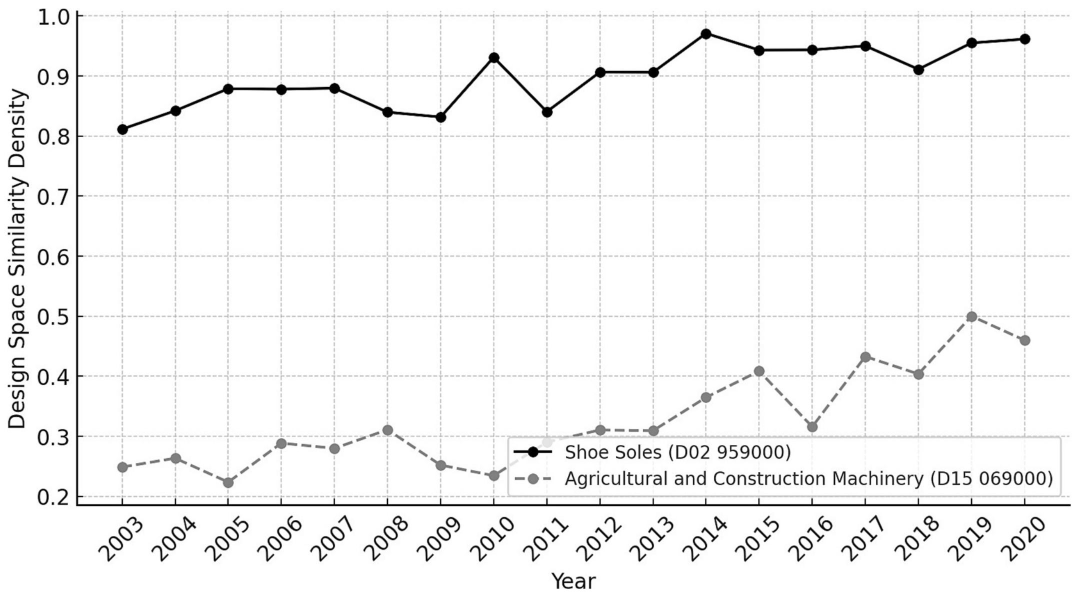

Fig. 3. Design space similarity density for shoe soles and for agricultural and construction machinery.

the possibility of such firm-level parameters (e.g., the average and variation in experience across firms in a design space) affecting filing strategies. Finally, we control also for the total number of attorneys in the subclass–year (*No. of Attorneys*) and thereby account for any influence they might have on filing outcomes.[16] Table 5 presents summary statistics for all our variables.

4.2. Design space similarity density and litigation

To start with descriptive results, Fig. 4 is a scatterplot of litigation rate (y-axis; the number of litigation cases per design right granted, over the entire observation period) against DSSD (x-axis), where each cross represents a design subclass. We observe that litigation is low at both ends of the DSSD spectrum (low and high similarity densities), with a clustering of cases in the DSSD's middle range. This pattern suggests an inverted–U-shaped relationship between DSSD and litigation, with litigation more frequent at moderate (than at extreme) levels of similarity density. We shall test this observation formally in the analysis that follows.

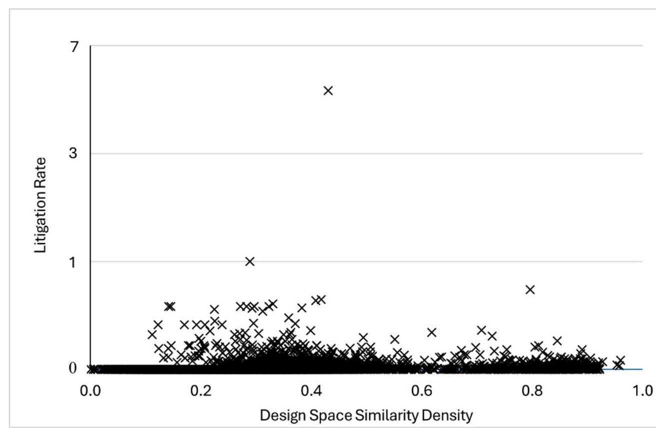

Fig. 4. Scatterplot of design space similarity density versus litigation.

Table 5
Summary statistics ($N = 22{,}550$).

Variable	Mean	SD	Min	Max
Litigation	0.371	1.941	0	151
DSSD	0.484	0.212	0.021	0.990
Design Filings	14.909	29.731	1	962
Ave. Firm. Designs	1511.822	1582.342	1	8328
Var. Firm. Designs	4,547,752	5,049,481	0	34,669,464
No. of Attorneys	16.775	31.970	1	1040
Year	2011.517	5.161	2003	2020

Note: The unit of analysis is the subclass–year.

Table 6 reports our results with subclass fixed effects (conditioned out with pseudo–maximum likelihood models) and also when controlling (or not controlling) for other parameters. All models point to the same insights. The effects can perhaps best be understood with reference to Fig. 5, which plots the marginal effects of DSSD and litigation count based on column [5] in Table 6. Observe first that the rate of litigation is initially increasing with DSSD: the slope is positive at the lower bound of DSSD (3.446; $p < 0.01$). Then the rate of litigation quickly stabilizes at a high rate near the middle at 0.568 before declining at high levels of DSSD—and at the DSSD's upper bound, the slope has become negative (−2.897; $p < 0.05$).

4.3. Robustness analyses

We conducted robustness checks using alternative estimation strategies. Whereas our baseline model employs Poisson pseudo–maximum likelihood models with *fixed* effects, column [1] of Table 7 tests the inverted–U-shaped relationship with *random* effects; this regression enables the testing of our insights while using all of our data (i.e., not merely data on the subset of design subclasses in which litigation is observed). Column [2] of the table replicates our insights while explicitly incorporating year fixed effects. Robustness of the inverted–U-

[16] Incumbent firms with greater access to financial and legal resources such as patent attorneys may tend to file and litigate more than smaller and younger firms (Somaya, 2012; Schartinger, 2023). A higher number of patent attorneys may therefore enhance the appropriability from IP, such as design rights (Reitzig and Puranam, 2009; Reitzig and Wagner, 2010). Thus, the number of patent attorneys may drive the litigation probability. It follows from our results that the number of patent attorneys is not a significant driver, and that our results are robust when including them (see Column [5] in Table 6).

Table 6
Design space similarity density and litigation ($N = 22{,}550$).

	[1]	[2]	[3]	[4]	[5]
DSSD	3.675***	3.815***	3.826***	3.836***	3.883***
	(1.088)	(1.140)	(1.148)	(1.125)	(1.127)
DSSD^2	−2.784**	−3.459***	−3.391***	−3.390***	−3.416***
	(1.126)	(1.207)	(1.226)	(1.227)	(1.223)
Design Filings		0.007***	0.007***	0.007***	0.011**
		(0.002)	(0.002)	(0.002)	(0.005)
Ave. Firm's Designs			−0.000**	−0.000**	−0.000**
			(0.000)	(0.000)	(0.000)
Var. Firm's Designs				−0.000	−0.000
				(0.000)	(0.000)
No. of Attorneys					−0.004
					(0.004)
Subclass FE	Yes	Yes	Yes	Yes	Yes
Log–pseudo–likelihood	−17,102.457	−16,951.680	−16,937.215	−16,937.181	−16,932.064

Notes: Fixed effects (FE) are conditioned out with Poisson pseudo–maximum likelihood models. Standard errors (in parentheses) are clustered at the subclass level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

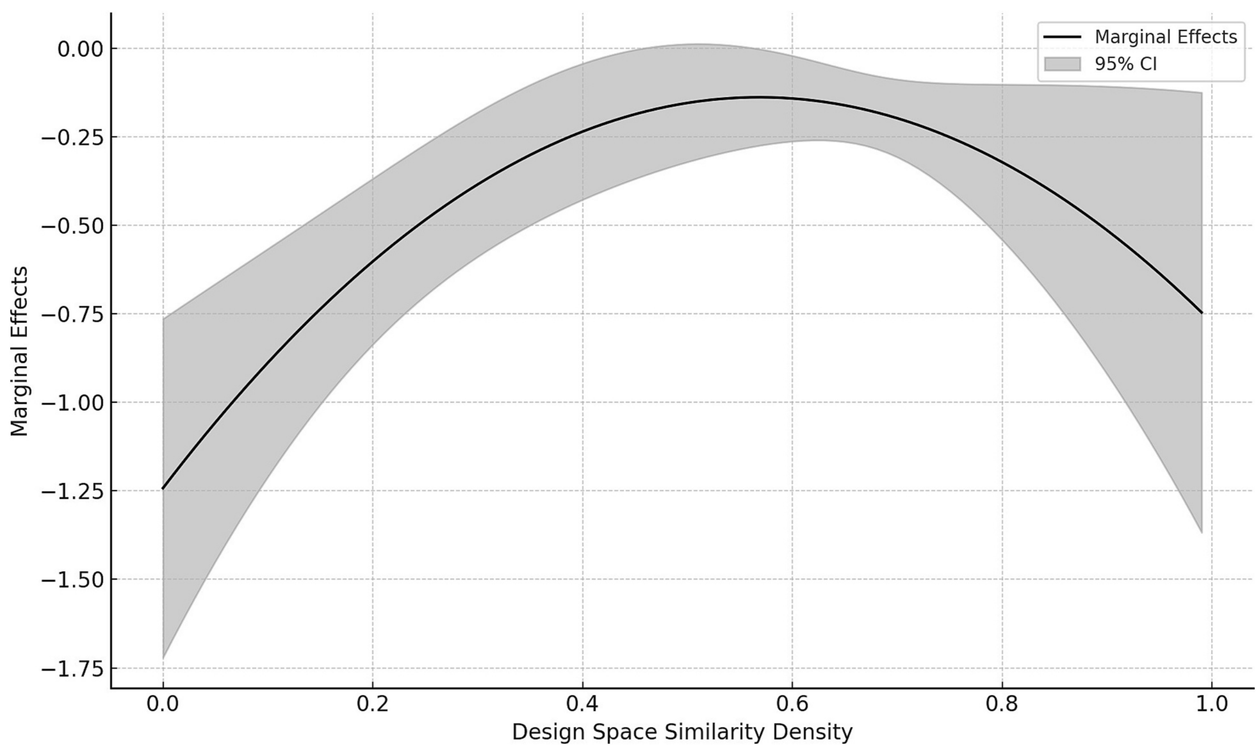

Fig. 5. Design space similarity density and litigation: marginal effects.

shaped relationship is confirmed across both specifications, underscoring the reliability of our core findings.

5. Discussion and conclusion

In today's competitive business environment, firms have come to recognize the strategic importance of design in enhancing their competitive differentiation, signaling unique product features, guiding novel product use, and fostering customer familiarity (Bu et al., 2022; Ching et al., 2024; Ghisetti et al., 2021; Landwehr et al., 2011; Mugge and Dahl, 2013; Mulder-Nijkamp, 2020). To protect their design rights, firms must not only file but also be willing and able to enforce them. Therefore, litigation plays a pivotal role in firms' strategic approach to IP rights protection (and to appropriation more generally).

Yet despite extensive research on drivers of litigation over patent rights—studies that have focused predominantly on firm-level parameters such as patenting capabilities (Reitzig and Wagner, 2010), superior firm resources (Agarwal et al., 2009), and patent law expertise due to in-house patent attorneys (Somaya and McDaniel, 2012) or on determinants such as country-specific institutional differences (Beukel and Zhao, 2018)—we have yet to develop a comprehensive understanding of the drivers of litigation related to design rights. This paper contributes a theoretically grounded and empirically validated industry parameter, *design space similarity density* (DSSD), that drives firms' likelihood of litigating. Our study shows empirically that DSSD has a curvilinear relationship with litigation, which accords with Filitz et al.'s (2015) prediction of an inverted U-shape. Our results also reflect the expected variations in DSSD across different design spaces (viz., machinery, shoes and mobile phones) and thus supports the notion that firms operating in different design spaces employ different design rights filing strategies (Filitz et al., 2015). In a nutshell, we establish that the design context in which a firm is embedded has a strong effect on whether that firm protects its rights through litigation or by alternative means.

We could not have obtained the results reported here without first

Table 7
Robustness checks.

	[1]	[2]
DSSD	6.631***	4.335***
	(1.457)	(1.258)
DSSD^2	−3.746***	−2.921***
	(1.255)	(1.096)
Design Filings	0.011**	0.010**
	(0.005)	(0.005)
Ave. Firm's Designs	−0.000***	−0.000**
	(0.000)	(0.000)
Var. Firm's Designs	0.000***	0.000**
	(0.000)	(0.000)
No. of Attorneys	−0.002	−0.003
	(0.004)	(0.004)
Subclass effects	RE	FE
Year FE	Yes	Yes
N	52,962	22,550
Log–pseudo-likelihood	−20,370.793	−16,750.900

Notes: Fixed effects (FE) are conditioned out with Poisson pseudo–maximum likelihood models. Standard errors (in parentheses) are clustered at the subclass level. RE = random effects.
** $p < 0.05$.
*** $p < 0.01$.

devising a measure of visual similarity between design rights. Thus a critical contribution is the measure we introduce for comparing and quantifying visual similarity across images, which can also be used to explore other variables of interest (e.g., as here, litigation and the value of a design right). Despite the increasing prominence of design rights in firms' strategies (Filitz et al., 2015; Heikkilä and Peltoniemi, 2019), and notwithstanding the easy access to proven methods of computer vision, there has been only limited application to the analysis of design rights. We bridge this gap and thereby contribute to innovation and strategy research—more specifically, to the literature on appropriation strategies—by introducing a design rights similarity measure that builds on an established measure for visual similarity (the SSIM). Our measure has been rigorously validated through extensive testing based on theoretically well-grounded validation strategies. Our measure can be applied to all common product categories and is extremely flexible in its application. We aim to foster further research by offering open access to our code and data, which contain pairwise similarity scores for more than 700,000 design rights documents.

We believe that our similarity measure can spur *research on design rights* in numerous directions to study the filing, litigation, and appropriation strategies of firms. Thus our work answers the call of Banks and Aguinis (2023) for introducing methodologies novel to the management community, thereby facilitating robust empirical research and advancing theoretical development. Further research might directly quantify how the various types and levels of indirect costs affect the filing for and (by extension) the disclosure of rights, and it could also examine how these parameters affect design similarity—and therefore strategic behavior—across design spaces.

Our design rights similarity measure can help explicate how similarity to prior designs affects the success of new technologies. According to the literature, designs that are more similar to those in the past may guide users on how to use novel products (Mugge and Dahl, 2013) while creating a sense of familiarity (Landwehr et al., 2011). The design rights similarity measure that we propose can inspire insight into why relying on past designs may be, perhaps counterintuitively, beneficial for firms that introduce radically new technologies—for instance, in the burgeoning field of green innovation. Last of all, our evidence suggests that DSSD increases over time. Thus the results not only support hypotheses suggestive of evolution in a firm's design rights filing strategy (as posited by Heikkilä and Peltoniemi, 2019) but also invite research that would help us better understand how increasing design similarity could relate to or even predict similarity of technological features in the evolution of a dominant design. Thus our approach could well be applied to analyzing certain types of image-based trademarks such as trade dresses or three-dimensional marks (Calboli, 2014; Castaldi, 2018; Flikkema et al., 2014, 2019).

These findings may also spur *research on patent rights*. Our analysis indicates that a firm's immediate industry and product context—in particular, the similarity density of the design space in which it operates—affects its decision to pursue litigation or to safeguard its rights through other means. We are not aware of any studies that analyze how a firm's filing strategy for patent rights may depend on the industry context in which the firm is embedded. This lacuna in the extant research is surprising when one considers (a) a design's potential to reveal key technological details (Ikeuchi and Motohashi, 2022) and (b) the well-established role of technological regimes (Cohen et al., 2000) in shaping firms' appropriation strategies. We therefore encourage scholars to apply our DSSD measure to the case of patent rights also.

In addition, our data and similarity measure may fuel research on *visual dimensions in strategy and management research* by opening new avenues by which to explore and understand the visual aspects of design and innovation within and across organizations (Boxenbaum et al., 2018). For example, scholars could apply our design rights similarity measure to assess, more accurately than before, the similarity of product design images or of the creative arts produced by generative AI—as benchmarked, perhaps, by human-generated design in visual communication (e.g., movie posters, logo designs).

Besides contributing to the literatures on innovation, strategy, and competitiveness, our findings may also guide policymakers. The existence of various filing and litigation strategies implies that policymakers would do well *not* to treat "design rights" as a homogeneous construct. This study hints that the current prices for design rights may be too low in some industries. Higher (but heterogeneously priced) design rights that reflect direct and indirect costs both would improve the functioning of any design rights regime. We remark that our measure delivers similarity scores rapidly, so it can be used by patent managers and examiners to search efficiently for similar prior art or by designers to identify design opportunities in design spaces that are relatively less dense.

There are three principal limitations of this study. First, we focus on the measurement of visual similarities across grayscale drawings (per the SSIM's original use case). Thus we do not analyze the measurement of visual similarities across color images. However, this limitation could be addressed by modeling how humans perceive two colors to be similar (or not) and then adding this dimension to our design rights similarity measure (i.e., supplementing brightness, contrast, and structure). Second, we use only the representative images presented on the first page of a design right. Future research should consider the feasibility of comparing product design drawings from different viewing angles or of constructing three-dimensional representations of a product design based on two-dimensional pictures. Finally, AI capacities in image processing are advancing rapidly (see e.g. Radford et al., 2021). Our design rights similarity measure could serve as a critical benchmarking tool for ensuring that AI-based algorithms perform efficiently and maintain high levels of structural integrity.

Yet even as we celebrate demonstrating that a tool—envisaged two decades ago—can measure similarity in a way that is useful for management research, we can only hold our breath in anticipation of the promising new approaches that will undoubtedly arrive. Having carefully measured visual similarity between design rights and then developed a similarity measure for large-scale empirical studies that rely on images, we hope that this new approach leads to opportunities for future research and also that we have made a valuable contribution to the "visual turn" now underway in management studies.

CRediT authorship contribution statement

Egbert Amoncio: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tian Chan:** Writing – review

& editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Cornelia Storz:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2025.105309.

Data availability

Data will be made available on request.

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