Social network and radical innovation: evidence from the U.S. pharmaceutical and biotechnology industry

Zhang, J.

CHAPTER 4

Patent radicalness and private value: Unpacking destructiveness and dissimilarity effects

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Author contributions:
Zhang, J. (Conceived and designed the analysis, Collected the data, Performed the analysis, Wrote the paper)
Wang, J. (Conceived and designed the analysis, Collected the data, Review and revised the paper)
Jong, S. (Review and revised the paper)

Abstract: Innovation is a key source of economic growth and firm competitiveness, but the economic impact of different innovations varies widely. In this paper, we study how the private value of a patent for the innovating firm is associated with its radicalness, differentiating between two dimensions of radicalness: destructiveness and dissimilarity. We argue that the private value is lower for patents that are more destructive to existing technology trajectories, because of their higher risk and uncertainty, longer road to profit, and incompatibility with existing firm capabilities. On the other hand, the private value is higher for patents that are more dissimilar to the exiting knowledge, due to the reception reward to novelty and ambiguity. Furthermore, dissimilarity makes it difficult for the market to understand the patented invention and therefore weakens the negative effect of destructiveness. These hypotheses are supported by a patent-level analysis of 1,066,637 USPTO granted patents.

Keywords: Patent; Radicalness; Destructiveness; Dissimilarity; Private value

4.1 Introduction

Studies of technological innovation have long distinguished between radical innovations that deviate from or obsolete existing technology trajectories and incremental innovations that only refine or improve existing technology trajectories (Dosi, 1982; Freeman, 1982; Henderson & Clark, 1990; Mansfield, 1968). Innovations vary in the degree of radicalness, which has important implications for not only innovation adoption and diffusion, but also firm organization and performance (Anderson & Tushman, 1990; Henderson, 1993; Henderson & Clark, 1990; Tushman & Anderson, 1986; Utterback, 1996). Scholars have extensively investigated the antecedents and consequences associated with these different innovation types (Ahuja & Morris Lampert, 2001; Arts et al., 2018; Arts et al., 2021; Bernal et al., 2019; Bourreau et al., 2012; Fazlıoğlu et al., 2019; Fleming, 2001; Funk & Owen-Smith, 2017; Kaplan & Vakili, 2015; Lopez-Vega & Moodysson, 2023; Schoenmakers & Duysters, 2010; Shane, 2001; Verhoeven et al., 2016). While many studies have focused on the social value of different types of innovations, namely the value for the whole economy and society, recent studies have explored how innovation radicalness is associated with private value for the innovating firm (Bartoloni & Baussola, 2018; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018). Understanding the relation between innovation radicalness and private value is important for informing firm strategy as well as innovation policies. However, empirical evidence is mixed.

One obstacle in reconciling competing theories and empirical evidence regarding innovation radicalness pertains to the diverse approaches for conceptualizing and operationalizing it. This is also reflected in the diversity of used terminologies in the literature (e.g., radical, novel, explorative, destructive, disruptive, unfamiliar, dissimilar) and measurement approaches (see Verhoeven et al. (2016) and Arts et al. (2021) for an overview).

In this paper, we differentiate between two important dimensions of innovation radicalness: destructiveness and dissimilarity. Destructiveness is about the degree to which a patented invention disrupts existing technology trajectories. Dissimilarity is about the degree to which a patented invention is dissimilar to existing knowledge. While destructiveness has important implications for firm performance, dissimilarity leads to perception biases in the valuation and diffusion processes in the marketplace.

We argue that destructive patents have a low private value for the innovating firm, because such patents are associated with higher risks and uncertainties, a longer road to profit, and incompatibility with existing firm capabilities. In contrast, dissimilar patents have a high private value because the market, when valuating technological innovation, has a preference for novelty and ambiguity in the cognition process. Furthermore, dissimilarity makes it more difficult for the market to understand information encoded in patents and in turn weakens the negative effect of destructiveness. These hypotheses are supported by our empirical analysis of 1,066,637 USPTO granted utility patents.

The contributions of this paper expand the literature on radical innovation. We highlight the importance of unpacking different dimensions of innovation radicalness (i.e., destructiveness and dissimilarity), which have distinct effects. Unpacking innovation radicalness also provides a useful approach for making sense of the diverse and sometimes competing theories and evidence about radical innovation.

The remainder of the paper is structured as follows. In section 2, we develop hypotheses concerning the effect of destructiveness and dissimilarity on private value, building on the literature on creative destruction and categorical theory. In section 3, we describe our sample, the variables, and the analyses we will conduct. In section 4, we present the results of descriptive statistical analysis, OLS regression, and quantile regression. In section 5, we discuss the implications of these findings and draw conclusions.

4.2 Theory and hypotheses

Firm innovation is considered the “fundamental impulse that sets and keeps the capitalist engine in motion” (Schumpeter, 1942). However, innovations come in different types, ranging from radical ones that are new and bring revolutionary changes to incremental ones that bring small improvements on existing technologies. Despite the rising interest in radical innovation, it remains an abstract and complex concept, easy to intuit but hard to define (Arts et al., 2021; Kaplan & Vakili, 2015; Verhoeven et al., 2016).

Radicalness is a multidimensional construct. For example, Dahlin and Behrens (2005) emphasized three defining features of radical innovation: novel, unique, and having a major impact on future technology. Verhoeven et al. (2016) distinguished between the ex ante and ex post characteristics of radical innovation, where the former is about being new or novel while the latter is about destructive impact. Different prior studies of radical innovation have focused on different aspects. Some have emphasized radical innovation as something that disrupts existing technology trajectories and accordingly has significant economic implications (Anderson & Tushman, 1990; Dosi, 1982; Henderson, 1993; Henderson & Clark, 1990; MartÍnez-Ros & Orfila-Sintes, 2009; Simms et al., 2021; Tushman & Anderson, 1986; Utterback, 1996; Verhoeven et al., 2016). Others have stressed radical innovation as something that is dissimilar to existing knowledge and accordingly faces perception penalties or rewards in its valuation and diffusion processes (Ferguson & Carnabuci, 2017; Kaplan & Tripsas, 2008; Kovacs et al., 2021; Polidoro, 2020; Rosenkopf & Nerkar, 2001). In this paper, we separate these two aspects and theorize their different effects on the private value of the innovation for the innovating company.

The literature on radical innovation spans several disciplines and uses inconsistent terminologies (i.e., sometimes use different terms for the same thing, while other times use the same term for different things), adding to the difficulty in making sense of seemingly competing theories and evidence in the literature. In this paper, we use more generic terms to label the two aspects of radical innovation to avoid confusion with other often-used terms. We label the ex post destructive characteristic of radical innovation as *destructiveness*[1] and the ex ante novel characteristic as *dissimilarity*[2].

4.2.1 Destructiveness and private value

One strand of literature on radical innovation focuses on the extent to which a technological innovation disrupts existing cognitive frameworks, technological trajectories, and organizational processes (Anderson & Tushman, 1990; Dosi, 1982; Henderson, 1993; Henderson & Clark, 1990; MartÍnez-Ros & Orfila-Sintes, 2009; Simms et al., 2021; Tushman & Anderson, 1986; Utterback, 1996; Verhoeven et al., 2016). Schumpeter (1942) coined the term "creative destruction" that "revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." Later studies have further differentiated innovation on a spectrum of varying degrees of destructiveness. On the one end, incremental innovations introduce minor changes to a current technology trajectory and enhance existing knowledge structures. On the other end, destructive innovations challenge existing ways of thinking and make incumbent technology

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[1] Some researchers might prefer the term "radicalness," especially the radical innovation scholars who focus on its ex post destructive impact. For example, Balachandran, S., & Hernandez, E. (2018). Networks and innovation: Accounting for structural and institutional sources of recombination in brokerage triads. *Organization Science*, *29*(1), 80-99. adopted the same measure as ours but labelled it as "radicalness." Some researchers might prefer the term "disruptiveness," as most studies adopting the same measure refer to it as "disruptiveness." However, "disruptive innovation" is a well-established term coined by Bower, J. L., & Christensen, C. M. (1995). Disruptive technologies: catching the wave. with two defining features: "First, they typically present a different package of performance attributes - ones that, at least at the outset, are not valued by existing customers. Second, the performance attributes that existing customers do value improve at such a rapid rate that the new technology can later invade those established markets." They are "usually not radically new or difficult from a technological point of view." The term of "disruptive innovation" has also been used in the literature broadly and inconsistently Si, S., & Chen, H. (2020). A literature review of disruptive innovation: What it is, how it works and where it goes. *Journal of Engineering and Technology Management*, *56*, 101568. https://doi.org/https://doi.org/10.1016/j.jengtecman.2020.101568 . Therefore, we use the more generic term "destructiveness."

[2] "Dissimilarity" in this paper has the same meaning as "novelty" in Dahlin, K. B., & Behrens, D. M. (2005). When is an invention really radical? Defining and measuring technological radicalness. *Research Policy*, *34*(5), 717-737. and Verhoeven, D., Bakker, J., & Veugelers, R. (2016). Measuring technological novelty with patent-based indicators. Ibid., *45*(3), 707-723. https://doi.org/10.1016/j.respol.2015.11.010 . However, "novelty" is also a complex concept and debated in the literature. We use the more generic term "dissimilarity."

obsolete (Chen et al., 2021; Funk & Owen-Smith, 2017; Trajtenberg et al., 1997).

Destructive innovation has been the subject of wide-ranging scholarly enquiries. Scholars have defined the destructiveness of inventions in terms of its profound impact on subsequent technological development. Previous studies have distinguished between competence-enhancing and competence-destroying (Anderson & Tushman, 1990), technology-consolidating and technology-destabilizing (Chen et al., 2021; Funk & Owen-Smith, 2017), sustaining and destructive (Christensen, 2013), and paradigm-deepening and paradigm-changing inventions (Ahuja et al., 2014; Dosi, 1982). Destructive inventions are defined as challenging the existing trajectories or paradigm (Anderson & Tushman, 1990; Chen et al., 2021; Funk & Owen-Smith, 2017). In this paper we follow this stream of literature and use the concept of destructiveness as describing the extent, to which new inventions consolidate or destabilize existing technology streams and shift inventors' attention away from the knowledge, on which inventions build.

Prior research has investigated how destructive innovation may impact firm performance (Anderson & Tushman, 1990; Henderson, 1993; Henderson & Clark, 1990; Tushman & Anderson, 1986; Utterback, 1996). Building on this literature, we focus on the private value of a technological innovation for the innovating firm and argue that destructive innovations have a lower private value for three reasons. First, destructive innovation is associated with high risks (MartÍnez-Ros & Orfila-Sintes, 2009). Destructive innovations are more likely to lead to high-performing breakthroughs, but at the same time are more likely to fail (Fleming, 2001; Singh & Fleming, 2010). Furthermore, destructive innovations also face a high level of unresolvable uncertainty or ambiguity (Simms et al., 2021; Ukobitz & Faullant, 2022). In other words, it is difficult for the innovating firm or the market to assign probabilities of success or failure for a destructive innovation ex ante (Shleifer & Vishny, 1997). Prior literature has found that individuals tend to be ambiguity-averse and discount uncertain outcomes (Fox & Tversky, 1995). Accordingly, due to the high level of risk and uncertainty associated with destructive innovations, we expect such innovations to be of lower private value for the innovating firm, compared with incremental innovations.

Second, the trajectory towards profitability tends to be longer for destructive innovations than incremental ones. Ideas that challenge existing status quo may a longer time to take off as these ideas require more follow-on research and development to realize their potential (Pezzoni et al., 2022; Wang et al., 2017). In addition to further technological development, capitalizing on destructive innovations requires a longer process of investments and accumulation of new skills and knowledge because destructive innovation "destroys" firms' existing competences (Anderson & Tushman, 1990; Simms et al., 2021; Tushman & Anderson, 1986; Utterback, 1996). Accordingly, we expect the delay in realizing the potential of a destructive innovation to contribute to its lower private value for the innovating firm.

Third, destructive innovations render existing competences obsolete (Henderson, 1993; Simms et al., 2021). Further developing destructive innovations requires new competences and routines that are distinct from a firms' existing ones. The innovating firm may fail in adopting the destructive innovation due to the incompatibility between the new destructive technology and the firm's existing competences and structures (Clark, 1987; Henderson & Clark, 1990). Therefore, even if the destructive innovation is promising and has a high social value (for the whole economy), the innovating firm might not be the firm to reap the rewards. In other words, while other firms, especially competitors and new entrants, might benefit from a destructive innovation, such an innovation often has a lower private value for the innovating firm due to its incompatibility with the innovating firm's existing competences.

Taken together, we hypothesize the following about the impact of an invention's destructiveness on the private value of this invention for the innovating firm.

> *Hypothesis 1: The destructiveness of a patent is negatively associated with its private value for the innovating firm.*

4.2.2 Dissimilarity and private value

The other defining feature of radical innovation emphasized in the literature is the extent to which an innovation output is new, dissimilar to existing knowledge, or unfamiliar to the audience. The degree of dissimilarity affects human cognition and therefore brings (positive or negative) reception biases in the process of innovation adoption or valuation. It is important to note that the dissimilarity of a technological innovation affects its private value for the innovating firm through very different mechanisms than that of destructiveness. More specifically, while destructiveness affects the true economic value of a technological innovation, dissimilarity biases the perceived value of a technological innovation.

How different audiences perceive and respond to certain products that are similar or dissimilar to those categorizing a certain market has been a central focus of the literature on classification systems in markets. According to this literature, classifications of existing activities provide an important low-effort mechanism for economic actors to make sense of complex social situations (e.g. Rosch, 1978). As the audience relies on established categories to identify and evaluate innovations, innovations that do not fit existing classification systems are confusing to the audience and subsequently face perception penalties (Zuckerman, 1999; Hsu et al., 2009; Zuckerman, 2003). Similarly, technological innovations that are dissimilar to existing technologies are likely to faces such perception penalties because they do not fit existing cognition frameworks and are difficult for the audience to comprehend.

However, an important distinction that is used to describe how different audiences respond to innovations that are dissimilar to existing activities categorizing a field, is the distinction between *market-takers* and *market-makers* (Pontikes, 2012). Market-takers rely on established categories to find or evaluate goods. Products or services that are more dissimilar are less appealing to market-takers that typically search for specific products or services and may employ evaluation criteria used for already existing products or services in assessing the value of innovations. Accordingly, market-takers discount innovations that are dissimilar to existing ones (Hsu, 2006; Hsu et al., 2009; Zuckerman, 1999).

In contrast, market-makers have an interest in innovations that can give rise to new markets. Market-makers include venture capitalists and investors who generally prefer innovations that are dissimilar from existing activities categorizing a field. Such innovations expand on the existing knowledge landscape and offer market-makers the prospect of novel offerings that open up new markets. Market-makers also value the ambiguity of dissimilar innovations. Dissimilar innovations potentially allow organizations to be more flexible and "multivocal" in appealing to more, different constituencies. Such appeal across different constituencies is of key value to organizations trying to construct novel fields under conditions of uncertainty (Padgett & Ansell, 1993). Leahey et al. (2017) highlight how market-makers differentially value innovations in the scientific realm. Their findings indicate that interdisciplinary studies are more highly cited by researchers. While Hirshleifer et al. (2018) find that the stock market undervalues firms engaging in innovation that is more *original* (i.e., citing more technology classes), Fitzgerald et al. (2021) observe that firms developing *unfamiliar explorative* patents (i.e., citing technology classes that are new to the firm) are relatively overvalued.

Taken together, we expect the market to respond more favorably to innovations that are more dissimilar from existing knowledge in a field and hypothesize that,

> *Hypothesis 2: The dissimilarity of a patent is positively associated with its private value for the innovating firm.*

4.2.3 Moderating effect of dissimilarity

Furthermore, dissimilarity is likely to moderate the negative effect of destructiveness on its private value. More specifically, for patents that are more dissimilar to existing knowledge, it is harder for the market to understand the new technology and recognize its destructive nature. According to sociological theory on the use of categories, products that do not fit existing classification systems are confusing to the audience and subsequently face perception penalties (Hsu et al., 2009; Zuckerman, 1999; Zuckerman et al., 2003). Information encoded in patents is complex, and it is challenging for investors to assess innovation disclosed in patents and its economic implications for firm value (Cohen et al., 2013; Hirshleifer et al., 2013, 2018). We expect this complexity to be enhanced for inventions that are more dissimilar to the pre-exiting knowledge base. Accordingly, while we have argued that the market is likely to respond positively to dissimilar inventions, we expect that a higher level of dissimilarity makes it more difficult for the market to ascertain the extent to which an invention is destructive. When an innovation is dissimilar from existing knowledge, it is harder for the market to understand its nature and assess its impact, including its potential of destructing existing technology trajectories. When the market has an impended ability to make an assessment, then we expect their negative response also to be mitigated. Therefore, we hypothesize that,

Hypothesis 3: The dissimilarity of a patent mitigates the negative association between destructiveness and its private value for the innovating firm.

4.3 Method and data

4.3.1 Data

To test our hypotheses, we integrate several datasets. We start from a dataset developed by Kogan et al. (2017) which covers granted USPTO utility patents up to 2010. Kogan et al. (2017) linked patent data to time series of stock prices and estimated the market value in millions of US dollars of each patent as the stock reaction to the event of the patent being granted by the USPTO. We link these patents to the PATSTAT (2019 Autumn Edition) database to retrieve citation links within USPTO for constructing the destructiveness measure. We also merge this dataset with the patent dataset developed by Arts et al. (2021), which extracted and cleaned keywords from patent title and abstracts, for measuring the dissimilarity of patents. In total, our sample covers 1,066,637 USPTO utility patents that were granted between 1980 and 2010.

4.3.2 Measures

Dependent variable

Private Value. The private value of each patent is retrieved from the patent dataset developed by Kogan et al. (2017). Kogan et al. (2017) linked patents to time series of firm stock prices, and estimated the private market value of each patent as the abnormal stock market return (in millions of US dollars) of the inventing company within a three-day window around the event that the patent is granted by the USPTO. Literature shows that a narrow time window is appropriate for capturing the private value of patents, since the increase in abnormal share turnover usually happens in the first two days after the announcement (Kogan et al., 2017). In addition, extending the time window may further introduce noises due to other events or influences. We use this estimated market value as our dependent variable, *private value*.

Independent variables

Destructiveness. For destructiveness we adopt the consolidating-destabilizing (CD) index proposed by Funk and Owen-Smith (2017). More specifically, this destructiveness measure examines whether patents citing a focal patent also cite its references. If patents citing the focal patent do not cite its references, then the focal patent is considered to reshape the network of technology interlinkages by shifting future inventors' attention away from the knowledge on which the focal patent builds, thus "disrupting" existing technology trajectories. For operationalization, the destructiveness measure retrieves all future patents that cite the focal patent or its referenced patents. Each citing patent is given a score: 1 if it cites the focal patent but not any patents referenced by the focal patent, -1 if it cites the focal patent and at least one of the patents referenced by the focal patent, and 0 if it does not cite the focal patent but does cite at least one of the patents referenced by the focal patent. The final destructiveness measure of a patent is a ratio, where the numerator is the sum of the scores across all the citing patents, and the denominator is the total number of these citing patents. This measure ranges between -1 (all the patents that cite the focal patent share some references with the focal patent, maximum consolidating) and 1 (none of the patents that cite the focal patent share any references with the focal patent, maximum destabilizing). For constructing this measure, we track all citation links between USPTO patents that are recorded in the PATSTAT 2019 Autumn edition. All future citing patents up to 2019 are considered. For a robustness test, we also use a fixed 5-year citation time window for calculating destructiveness, where only future citing patent within 5 years after the grant date of the focal patent are taken into account. Results are robust.

Dissimilarity. Following Arts et al. (2021), we measure the dissimilarity of a patent based on text similarity between a patent and all prior patents filed in the five years before the focal patents. More specifically, we retrieve all patent keywords for each patent, and then calculate the text similarity between a pair of patents as the cosine similarity between their vectors of keywords. At the patent level, we take the average cosine similarity between a focal patent and all prior patents filed in the five years before the focal patent. Since the cosine score is about similarity, which is the opposite to being dissimilar, we transform the measure by subtracting it from 1. The final variable, *dissimilarity*, ranges from 0 (i.e., perfect overlap in keywords between the focal patent and prior patents; maximum similarity) to 1 (i.e., no overlap in keywords at all; maximum dissimilarity). We also tried alterative measures such as the share of new keywords or new keyword pairs that never occurred before, and obtained robust results.

Control variables

For regression analysis, we adopt the model specification from Kogan et al. (2017) and Poege (2019). More specifically, we control for several variables that are potential confounders. There are important differences between technology fields and years, to account for these differences, we incorporate technology class-grant year pair-level fixed effects, to absorb variation across fields and year dimensions, following prior studies. We control for the number of patent references, as building on the broader set of prior technologies might lead to higher economic value on the one hand and higher or lower destructiveness and dissimilarity on the other. For the same reason, we control for the number of patent citations. However, it is unclear whether patent citations should be controlled for as this variable goes longer into the future than the Private Value variable, and is oftentimes used as a measure of patent value by itself (Hall et al., 2005; Harhoff et al., 2003). Therefore, we also tested the robustness of our results without controlling patent citation and obtained consistent results.

4.4 Results

4.4.1 Descriptive statistics and nonparametric analysis

Descriptive statistics and correlations are reported in Table 4.1. The average *private value* of our sampled patents is 23.974 million US dollars, and the distribution of *private value* is highly skewed, so that we take natural logarithm transformation for correlation and regression analysis. *Destructiveness* ranges between -0.958 and 0.997, while the maximum possible range is between -1 and 1. *Dissimilarity* ranges from 0.895 and 1, which is relatively high considering that the maximum possible range is between 0 and 1. This is understandable, as one important criterion of patentability is novelty in the sense of being different from prior art. Nevertheless, there is still variance in dissimilarity across patents for analysis. We observe that patent *private value* is negatively correlated with *destructiveness* (r = -0.092) but positively correlated with *dissimilarity* (r =0.161). Correlations among independent variables are all moderate, so we are not worried about multicollinearity, except that the correlation between *destructiveness* and *citations* is relatively high (r = -0.399). Together with the reasons discussed in the control variables subsection, we added a robustness check to run regressions without controlling for patent citations and obtained consistent results.

Table 4.1: Descriptive statistics and correlations (N = 1,066,637)

	Variable	Mean	S.D.	Min	Max	1	2	3	4
1	Private value (m$)	23.974	73.778	0.000	6208.359				
2	Destructiveness	0.063	0.140	-0.958	0.997	-0.092			
3	Dissimilarity	0.967	0.012	0.895	1.000	0.161	-0.037		
4	Citations	13.815	16.985	1.000	119.000	0.121	-0.399	0.018	
5	References	29.400	54.785	1.000	5537.000	0.141	0.147	0.004	0.128

Note. Private value, Citations and References take natural logarithm transformation before calculating correlations.

Before reporting regression results, we first use a non-parametric approach to analyze the data. To account for differences across fields and years, as well as to accommodate the skewness in the dependent variable, we first transform *private value* into an ordinal ranking variable, *private value rank*. More specifically, within each technology class and grant year pair, we rank patents by their *private value*, where a patent with the lowest *private value* is ranked as 0, and the one with the median *private value* is ranked as 0.5, and the one with the highest *private value* is ranked as 1. The resulting *private value rank* variable follows a uniform distribution. For our focal independent variable *destructiveness*, we partition patents into five quintiles, where the first quintile consists of patents with the lowest 20% destructiveness scores within each technology class and grant year pair, and the fifth quintile consists of patents with the highest 20% destructiveness scores within the same technology class and grant year. We do the same for *dissimilarity*. Figure 4.1 shows the distribution of *private value rank* by *destructiveness* and *dissimilarity* quintiles. The third quintile consists of the 20% patents with middle *destructiveness* scores, within this quintile of patents, the distribution of *private value rank* largely resembles a uniform distribution. When destructiveness is lower (i.e., the first and second quintile), the share of patents with high private value increases while the share of patents with low private value decreases, suggesting an advantage in private value for less destructive patents. A consistent pattern is observed when destructiveness is higher (i.e., moving to the fourth and fifth quintile). Furthermore, we observe a bipolar distribution of *private value rank* among the patents in the fifth quintile of *destructiveness*. In other words, when *destructiveness* is very high, patents are more likely to have very low or very high private value but relatively less likely to be in the middle. This is consistent with the higher level of risk and uncertainty associated with highly destructive inventions. Regarding *dissimilarity*, we observe that as *dissimilarity* increases, the mass of patents shifts from low private value to high private value.

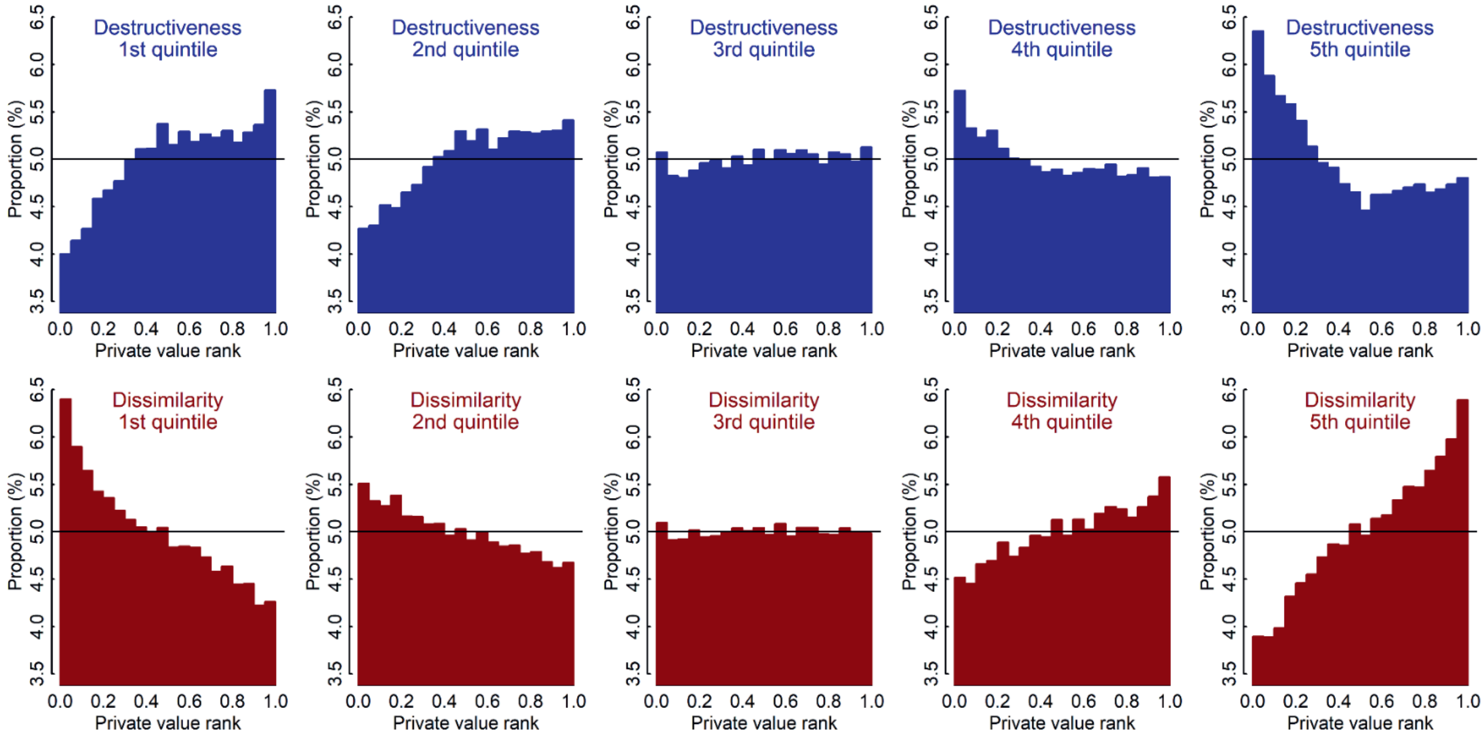

Figure 4.1: Distribution of private value by destructiveness and dissimilarity quintiles.

4.4.2 Regression results

We run regression analysis to test the effect of *destructiveness* and *dissimilarity* on *private value*, at the patent level, controlling for the number of citations, references, and technology class-grant year pair-level fixed effects. The dependent variable is skewed, and we take its natural logarithm and run OLS regressions. To facilitate comparing effect sizes of *destructiveness* and *dissimilarity,* these two variables are standardized for regression. Thus, the coefficient represents the change in the dependent variable as *destructiveness* or *dissimilarity* increases by 1 standard deviation. Number of citations and references also take natural logarithm transformation, following standard practice.

Regression results are reported in Table 4.2. Model (1) focuses on the effect of destructiveness without controlling for dissimilarity. Comparing patents in the same technology class and year, and with the same number of references and citations, when the destructiveness of a patent increases by 1 standard deviation, patent private value decreases by 14.3%, which is an economically sizable change. Model (2) suggests that 1 standard deviation increase in patent dissimilarity is associated with 19.6% increase in patent private value. Model (3) analyzes destructiveness and dissimilarity, and the size of coefficients is comparable to Model (1) and (2) when analyzing them separately. Therefore, both Hypothesis 1 and 2 are supported by the empirical analysis.

Table 4.2: Destructiveness, dissimilarity, and private value

	ln(Private value) OLS			
	(1)	(2)	(3)	(4)
Destructiveness	-0.143***		-0.140***	-0.141***
	(0.004)		(0.004)	(0.004)
Dissimilarity		0.196***	0.193***	0.193***
		(0.006)	(0.006)	(0.006)
Dissimilarity * Destructiveness				0.023***
				(0.003)
ln(References)	0.082***	0.153***	0.092***	0.091***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Citations)	0.237***	0.209***	0.235***	0.235***
	(0.005)	(0.004)	(0.005)	(0.005)
Patent class * Year fixed effects	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637
R-square	0.204	0.206	0.209	0.209

Note. Destructiveness and dissimilarity are standardized. Robust standard error clustered at patent class * year level in paratheses. *** p<.001, ** p<.01, * p<.05.

In Table 4.2 Model (4) we further interact destructiveness and dissimilarity. Results show a significantly positive interaction effect. This means, as dissimilarity increases, the negative effect of destructiveness on patent private value shrinks. To better understand the moderating effect of dissimilarity, we plot the marginal effect (i.e., coefficient) of destructiveness at different levels of dissimilarity (Figure 4.2A). As shown in Figure 4.2A, as dissimilarity increases, the effect of destructiveness remains negative but the effect size is smaller. This supports Hypothesis 3.

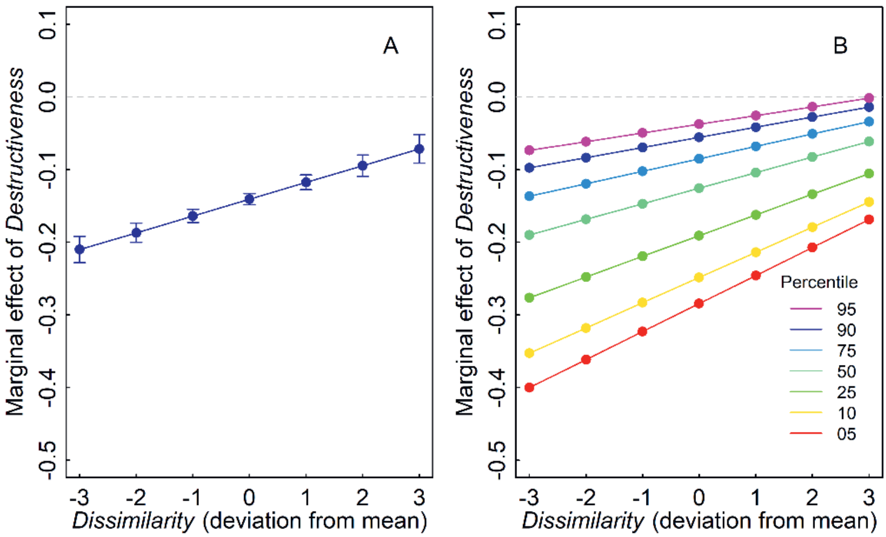

Figure 4.2: Dissimilarity moderates the effect of destructiveness on private value.

OLS estimates effects on the mean of *ln*(*private value*), we further investigate potential differences in effects at different percentiles *private value*. It is possible that as *destructiveness* increases, patents are more likely to have very low or high private value but less likely to have median private value. Then we should observe a positive effect at low and high quantiles of the dependent variable, but negative effects at median quantiles. Quantile regressions use the same model specification as OLS regression (control variables and variable transformations) but model different quantiles of the dependent variable instead of the mean. Considering the heterogeneity of innovation returns, quantile regression can be used to explore a more complete picture of the radicalness-market response relationship, which may provide us new sights to understand the relationship between destructiveness, dissimilarity, and private value. Results are reported in Table 4.3. Results suggest consistent negative effect of destructiveness across all quantiles of private value. The size of the coefficient is larger at lower quantiles than higher quantiles, and this should be interpreted with great caution. Decrease by 28.4% is much more substantial than decrease by 3.8%. However, the 5th percentile of private value is 0.0463 and the 95th percentile is 93.954. Then a 28.4% decrease at the 5th percentile and 3.8% decrease at the 95th percentile correspond to a drop of 0.013 and 3.570 million US dollars. Therefore, depending on the criterion (size of change in percentages or absolute values), the conclusion about whether the effect size is larger at low or high quantiles can be opposite. Therefore, we only conclude from this set of results that there is a consistently positive effect of dissimilarity on private value. Similarly, we also observe a consistently negative effect of destructiveness, and a consistently positive interaction effect between dissimilarity and destructiveness (Figure 4.2B). In summary, the quantile regression results do not provide evidence that the effects are qualitatively different at different quantiles of private value.

Table 4.3: Destructiveness, dissimilarity, and private value: Quantile regression

	ln(Private value) Quantile regression						
	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
Destructiveness	-0.284***	-0.249***	-0.191***	-0.126***	-0.085***	-0.056***	-0.038**
	(0.042)	(0.035)	(0.022)	(0.009)	(0.003)	(0.007)	(0.011)
Dissimilarity	0.317***	0.286***	0.236***	0.180***	0.145***	0.120***	0.104***
	(0.041)	(0.034)	(0.022)	(0.008)	(0.003)	(0.007)	(0.011)
Dissimilarity * Destructiveness	0.039	0.035	0.028	0.021**	0.017***	0.014*	0.012
	(0.037)	(0.030)	(0.019)	(0.007)	(0.002)	(0.006)	(0.010)
ln(References)	0.238***	0.201***	0.142***	0.076***	0.034***	0.004	-0.014
	(0.044)	(0.036)	(0.023)	(0.009)	(0.003)	(0.008)	(0.012)
ln(Citations)	0.440***	0.389***	0.307***	0.214***	0.156***	0.114***	0.088***
	(0.033)	(0.027)	(0.017)	(0.007)	(0.002)	(0.006)	(0.009)
Patent class * Year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	1066637	1066637	1066637	1066637	1066637	1066637	1066637

Note. Dissimilarity and destructiveness are standardized. Robust standard error clustered at patent class * year level in paratheses. *** $p<.001$, ** $p<.01$, * $p<.05$.

4.4.3 Robustness tests

We run a set of further analyses to test the robustness of our results. First, we drop the number of citations as a control variable in regression analysis. This is partly due to the multilinearity concerns warned by the high correlation between destructiveness and citations. Furthermore, whether citation count is a confounder in this setting is unclear. Some might argue that citations capture the technological merit of the invention, which affects both radicalness (i.e., destructiveness and dissimilarity) and private value. Some might think that radicalness affects citations which in turn affects private value. Others might think that citation count is another measure of patent value similar as the dependent variable itself. For the reported main results, we choose to control for citations so that we can have a stricter estimation of the effects of destructiveness and dissimilarity when comparing patents with the same number of citations. For a robustness test we use a more relaxed approach and not control for citations. Results are robust (Appendix Table C1).

Second, we use a fixed 5-year time window for counting forward citations and calculating the destructiveness. The reported main results use all forward citing patents up to 2019, and patents in different years have different number of years for accumulating citations, which is accounted by incorporating patent year fixed effects. Nevertheless, we test whether using a shorter and fixed citation time window would lead to the same results. Results are robust (Appendix Table C2), and effect sizes are comparable.

Third, we test an alternative formulation of the destructiveness measure. More specifically, building on the network betweenness centrality concept, Shibayama and Wang (2020) proposed an originality measure for individual scientific publications to capture the degree to which a scientific discovery provides subsequent studies with unique knowledge that is not available from previous studies. It is operationalized as the share of missing ties in the network consisting of the focal patents and all its citing and cited patents, where a tie is a citation link. We adopt this measure for patents and obtain robust results (Appendix Table C3).

Fourth, we also test alternative measures of dissimilarity. Following Arts et al. (2021), and the combinatorial novelty perspective, dissimilarity of a patent can also be captured by its share of new keywords that never occurred in prior patents and its share of new keyword pairs that never occurred in prior patents. Using these two alternative measures of dissimilarity yields robust results (Appendix Table C4, Table C5).

4.5 Discussion and conclusion

This paper studied the relation between patent radicalness and private value for the innovating firm. More specifically, we differentiated between patent destructiveness and dissimilarity and investigated their differential effects on patent private value. Using a set of 1,066,637 USPTO granted utility patents, we adopted the market value of individual patents based on abnormal changes in firm stock price shortly after the event that a patent is granted, developed by Kogan et al. (2017). We measured the destructiveness of patents using citation networks and more specifically the extent to which a patent destabilize the existing flows, following Funk and Owen-Smith (2017) and the dissimilarity of patents based on to what extent the text of a patent is dissimilar to prior patents, following Arts et al. (2021). We found a negative association between patent destructiveness and private value. This suggests that destructive innovation might bring lower private value for the innovating firm due to its high levels of risk and uncertainty, the longer road to profit, and the incompatibility between destructive innovation and innovating firm's existing capabilities. In contrast, we found a positive association between patent dissimilarity and private value, suggest a reception premium for novelty and ambiguity. Furthermore, patent dissimilarity leads to more difficulties for the market to understand the patented invention and therefore weakens the negative effect of destructiveness on patent private value.

This paper has several limitations. First, although patent data provide an ideal setting for testing our hypotheses, our empirical analysis cannot avoid issues that are common to all studies relying on patent data. For example, many unimportant inventions are failed to be patented, and some breakthroughs may be missed due to firms' strategic reasons (Fleming, 2001). While granted patents are not a perfect archive of technological innovations, the data still represent a considerable share of invention outputs with varying degrees of radicalness. Future research adopting a broader set of innovation outputs would be valuable to extend from patents to other innovative outputs.

Second, we follow Kogan et al. (2017) in measuring patent private value as the stock market reaction to the news that the patent is granted. This measure is only available for patents of publicly traded firms, while patents of private companies, non-profit organizations and governments are ignored. Caution should be taken when generalizing our findings to non-listed companies or institutions, and it may be interesting for future work to test whether our findings are applicable to other types of organizations. In addition, it is difficult to evaluate the exact stock prices for each patent, because the same stock prices are allocated to all patents of the same assignee that were granted on the same day. Future research may further improve the accuracy of the patent private value measure.

Third, we focus on two dimensions of radicalness: i.e., destructiveness and dissimilarity, while radicalness may encompass other aspects or dimensions, it would be interesting for future studies to explore other dimensions and related mechanisms. Fourth, we do not capture the dynamic process through which the technological, economic, and societal impact of a patent invention unfolds. We only study the short-term private value of a patent depending on its dissimilarity and destructiveness. It would be interesting to investigate effects of dissimilarity and destructiveness in longer terms and beyond the innovating firm (i.e., social value).

Nevertheless, this paper makes several theoretical contributions. First, we add to the fast-expanding literature about radical innovation. While prior studies have investigated various technological and economic consequences of radical innovation (Ahuja & Morris Lampert, 2001; Arts et al., 2018; Arts et al., 2021; Fleming, 2001; Funk & Owen-Smith, 2017; Kaplan & Vakili, 2015; Schoenmakers & Duysters, 2010; Shane, 2001; Verhoeven et al., 2016), we explore its effect on patent private value.

Second, we unpack the abstract concept of radicalness and make an important distinction between destructiveness and dissimilarity, which affect patent private value in distinct manners and interact with each other. This provides a useful approach for reconciling seemly conflicting empirical findings in previous literature (Cohen et al., 2013; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018). Radical innovation is a complex and composite concept, and explicitly differentiating its dimensions is essential for a better understanding of it.

Third, accompanying the differentiation between destructiveness and dissimilarity is the separation between (a) theories focusing on substantive technological and economic consequences of destructiveness due to its association with risk/uncertainty and profitability and (b) theories focusing on reception biases related to dissimilarity due to cognition difficulties. These theories explain different aspects of the phenomenon, and integrating them helps us to better understand outcomes that emerge from multiple complex processes, such as private value in terms of stock returns, which depends on true economic value and perception biases.

Our findings also have implications for innovation policy and management. From a practitioner standpoint, it is important to understand consequences of different types of innovation. The negative association between destructiveness and private value warns companies about risks and uncertainties associated with conducting destructive innovation. Companies that engage in such innovation need to carefully manage its higher level of risk and uncertainty, longer time period needed to make it profitable, and potential incompatibilities with existing capabilities. Our findings also shed light on potential biases and sources of mispricing in the stock market. Consistent with prior studies (Cohen et al., 2013; Fitzgerald et al., 2021; Hirshleifer et al., 2013, 2018), our findings suggest that it is difficult for the stock market to understand patented inventions, especially dissimilar ones, for assessing its implications on firm value. Investors should be aware of these difficulties and carefully mitigate associated biases. Innovating companies should also pay attention to how to disclose their innovation and manage market expectations.