Technovation 136 (2024) 103070

Contents lists available at ScienceDirect

Technovation

journal homepage: www.elsevier.com/locate/technovation

Pricing innovation: The anchoring effect in patent valuation

P.E.N.G.F.E.I. Wang

Department of Strategy and Entrepreneurship, BI Norwegian Business School, 0484 Oslo, Norway

ARTICLE INFO

Keywords:
Patent
Valuation
Anchoring
Value
Novelty

ABSTRACT

Prior literature has long recognized the substantial economic value that patents hold in the market. Yet, we know much less about the valuation process, i.e., how market audiences estimate (or determine) the value of newly granted patents. Building on behavioral economics, we propose the anchoring effect as an important cognitive mechanism, such that a patent's valuation is anchored on the value that preceding patents have secured. Analyzing financial valuation of U.S. patents between 1991 and 2010, we find broad support to the anchoring effect. The effect is more pronounced when focal patents are of lower novelty, when prior anchors are more consistent, and when focal firms have a higher patenting frequency. Furthermore, our extensional analysis suggests that anchoring acts as an important driver for the divergence between patents' economic value and scientific quality, which deserves attention from firms and policy makers.

1. Introduction

Because technological innovation is a key driver of value creation and economic growth (Schumpeter, 1983), patents, as an important form of upstream innovation outputs, usually carry considerable economic or financial value (Hall and Harhoff, 2012; Hirshleifer et al., 2018). Extensive research has been conducted to investigate the private economic value of patents (*patent value* for short) (Gambardella, 2013).[1] Some studies emphasize how to more precisely quantify parent value (Abrams et al., 2013; Bessen, 2008; Giuri et al., 2007; Kogan et al., 2017); others strive to identify the key antecedents of it (Harhoff et al., 2003; Huang et al., 2021). Despite the important progresses, however, extant research focuses mostly on the characteristics of focal patents and firms (Arora et al., 2023; Gambardella et al., 2008; Odasso et al., 2015), assuming that these inherent factors (e.g., citations, claims, class, and firm size) will predominantly determine the economic value of patents. Much less has been discussed about the way how the market actually valuates patents. Overlooking market valuation mechanisms is a bit unfortunate, since scholars have long suggested that economic value is largely shaped and revealed by how market audiences make sense of patents (Bessen, 2009; Kogan et al., 2017; Rindova and Petkova, 2007).

To extend research along this line, we emphasize that patent value depends not simply on their inherent characteristics, but more importantly on the cognitive valuation processes adopted in the market. Specifically, building upon behavioral economics (Beggs and Graddy, 2009; Tversky and Kahneman, 1974), we introduce the anchoring effect as a potential mechanism in patent valuation, wherein market audiences will anchor on preceding patent valuation to estimate the value of focal patents. Empirically, we analyze how stock markets react to the approvals of U.S. patents (Kogan et al., 2017), and find broad evidence to the anchoring effect, even after controlling for patents' inherent attributes. Further analyses of scope conditions show patterns that are also consistent with our proposed anchoring effect: anchoring is found to be particularly strong when focal patents are of lower novelty, when prior anchors are more consistent, and when focal firms have a high patenting frequency. By doing so, our study extends the current literature in several ways.

First, to gain a deeper understanding of patent valuation, we draw attention from patent characteristics to market valuation mechanisms. While extant studies underscore the importance of investigating patent value (Gambardella, 2013), most of them focus on the inherent features of patents. Patent value, for instance, has been found to be associated with backward citations, claims, and technology classes, as well as family size, firm size, and firm ownership types (Arora et al., 2023; Bessen, 2008; Gambardella et al., 2008; Harhoff et al., 1999; Huang et al., 2021; Odasso et al., 2015). While important, however, these characteristics are found to only account for partial variance of patent value, leaving a vast majority of value variance unexplained (Gambardella et al., 2008). The limited explanatory power of patent characteristics is not surprising, because their associated value is

E-mail address: Pengfei.wang@bi.no.

[1] Unless specially stated, patent value is used in this paper to denote the private *economic* value of patents (Arora et al., 2023; Gambardella et al., 2008; Kogan et al., 2017). It is hence different from technological value/quality, which reflects how much technological progress that patents make.

https://doi.org/10.1016/j.technovation.2024.103070
Received 30 July 2023; Received in revised form 22 May 2024; Accepted 7 July 2024
Available online 16 July 2024

ambiguous for anyone in the market but a select few expects (Chemmanur et al., 2022). We argue that to better understand the economic value of patents, it is necessary to investigate the valuation mechanisms employed in the market, because patent value is subject to the way how market audiences perceive and evaluate them (Rindova and Petkova, 2007), rather than a simple reflection of their inherent characteristics.

Second, and more importantly, emphasizing the uncertainty of patent valuation, we posit that cognitive heuristics will be activated when audiences estimate the value of patents. Specifically, we highlight the anchoring effect as a possible mechanism through which patents are valuated. Anchoring is a ubiquitous heuristic by which estimates are anchored on the preceding information (i.e., anchor) (Tversky and Kahneman, 1974). While scholars have found solid evidence for it in various experimental and social contexts, recent studies show that anchoring is also prevalent in the market valuation process (Malhotra et al., 2015; Northcraft and Neale, 1987). However, there is no research, to our best knowledge, that brings the anchoring perspective to patent valuation. By presenting anchoring as a prominent mechanism in patent valuation, our study directs attention from patents' attributes (Gambardella, 2013) to cognitive heuristics that shape market audiences' sensemaking and judgment.

Finally, by underscoring the anchoring effect, this research may also help explain the decoupling between economic and scientific value of patents. While the economic and scientific value of patents usually align with each other (Hall et al., 2005; Harhoff et al., 1999; Kogan et al., 2017), they are also found to be substantially divergent (Abrams et al., 2013; Bessen, 2008; Higham et al., 2021). The mainstream explanation focuses on their distinct nature: economic and scientific value are determined by the same characteristics in different ways. For instance, citations to foreign patents are found to be very important for economic value, but not for scientific value (Higham et al., 2021); firm size increases economic value, but decreases scientific value (Arora et al., 2023). Adding to this stream, we emphasize that the divergence may also be driven by anchoring, which brings considerable subjectivity and social construction into the valuation process. More specifically, because patent valuation is anchored on preceding patents, rather than only on focal patents' characteristics, potential "bias" is likely to be introduced, thereby driving apart their economic and scientific value. Such "bias" deserves policy makers' attention, as high-quality innovations may be discouraged in a market with substantial divergence between patent quality and valuation.

2. Theory and hypotheses

One of core topics in the innovation literature is how to quantify the value of innovations (Harhoff et al., 1999; Trajtenberg, 1990). Value is broadly defined as an innovation's worth in a particular social context (Rindova and Petkova, 2007). Whereas some scholars focus on the scientific/technological value of innovations, by primarily examining the forward citations of patents (Fleming et al., 2007; Kaplan and Vakili, 2015; Kok et al., 2019); others emphasize the estimate of economic value that patents bring to their holders (i.e., *patent value* hereafter) by employing a wide range of creative measures (Gambardella et al., 2008; Hall et al., 2005; Harhoff et al., 2003; Kogan et al., 2017).

Analyzing patent value is important for several reasons. First, because patents represent a significant portion of intellectual properties of firms (and economies), estimates of patent value help more precisely assess their intangible assets (Gambardella et al., 2008). This may be particularly important for small firms that depend mostly on intangibles in the process of raising capital (Hsu and Ziedonis, 2013). Second, understanding patent value is also relevant for many inter-firm transactions such as cross-licensing, strategic alliances, or joint ventures, where patent-related contract terms are usually set according to their economic value (Abrams et al., 2013; Lerner et al., 2007). Furthermore, policy makers are also interested in patent valuation, so as to design better systems (e.g., targeted R&D subsidies) to promote high-quality innovations (Bronzini and Piselli, 2016).

Given its importance, scholars have made effort to investigate patent value. While some use the number of forward citations as a simple proxy (Kaplan and Vakili, 2015), others have developed specific measures for patent value in different ways. One traditional approach, for instance, utilizes heterogeneity on patent renewals (Bessen, 2008), assuming that patent that are not renewed carry economic value less than renewal fees. Recognizing the limitations of using renewal data (e.g., underestimating heterogeneity in the extreme right tail of distribution), Harhoff and colleagues employ a survey-based measure by asking inventors to estimate the minimum price that they would demand if selling a patent to competitors (Gambardella et al., 2017; Harhoff et al., 2003); Abrams et al. (2013) leverage unique data on patent licensing fees from large non-practicing entities to estimate patent value. Recently, scholars take advantage of data on asset pricing in the public market to infer patent value (Hall et al., 2005; Hirshleifer et al., 2018). Specifically, in their seminal work, Kogan et al. (2017) use stock market responses to announcements about patent approvals to develop a very useful proxy for the private valuation of patents at the time of approvals.

In addition to quantifying patent value, scholars have also devoted considerable attention to uncovering the key determinants of it. Specifically, prior studies show that patent value is significantly associated with a broad range of patent characteristics, including the number and types of backward citations, technological claims, innovation originality and generality, family size, portfolio size, knowledge synthesis, as well as the features of patenting firms (Arora et al., 2023; Bessen, 2008; Gambardella et al., 2008, 2017; Harhoff et al., 2003; Higham et al., 2021; Huang et al., 2021). Interestingly, many of those patent characteristics are associated with patents' scientific value (or quality) as measured by forward citations. As such, we often observe a high association between their economic and scientific value (Kogan et al., 2017). This is not surprising, since patents' economic value should be largely, though not perfectly, contingent on how much scientific advancement they make (Hall and Harhoff, 2012).

However, Higham et al. (2021)'s study highlights that the same patent characteristics can have very different impacts on economic and scientific value, respectively. For instance, technological novelty is significantly associated with patents' scientific value, but less so with economic value; combining international knowledge is useful to enhance economic value, but not scientific value. Their important work implies that patents' economic value may not be predominantly determined by their scientific advancement or patent characteristics (Abrams et al., 2013). If so, what else is shaping the valuation of patents, beyond patent and firm attributes?

To shed light on this, we draw attention to the valuation mechanisms employed by market audiences (e.g., investors, customers, and competitors). Patents bring more private economic value when audiences perceive more worth from and attribute more credits to them, and vice versa (Kogan et al., 2017). Because audiences' perception and valuation are subject to behavioral factors (Rindova and Petkova, 2007; Tversky and Kahneman, 1974), a patent's economic value is essentially a result of their cognitive judgment, which can potentially decouple from the patent's inherent characteristics and scientific quality. Specifically, we propose the anchoring effect as an essential mechanism that drives audiences' estimate of patent value in the market.

2.1. Anchoring and patent valuation

When facing uncertainty, people usually opt for judgmental heuristics in their intuitive and rapid system, which help reduce the complexity of value estimates to simpler evaluative operations (Tversky and Kahneman, 1974). One of the most pervasive cognitive heuristics is the anchoring effect (Furnham and Boo, 2011). It suggests that under uncertain conditions, people tend to set an anchor on prior information and then make adjustments around it which are usually insufficient, such that their final estimate is manipulated by the anchor than it would be without the anchor (Malhotra et al., 2015). The anchoring effect is found remarkably robust, as it occurs even when anchor value is clearly irrelevant or extreme (Strack and Mussweiler, 1997; Tversky and Kahneman, 1974) and/or people have high motivation and expertise for the best estimates (Northcraft and Neale, 1987).

While earlier evidence of anchoring is mostly found from laboratory experiments, it is pervasive for decisions and estimates in real-world settings, especially in the valuation processes that are inherently uncertain. Indeed, Northcraft and Neale (1987) show that in estimating house value, real estate agents are largely directed by the manipulated listing price, even if they have all the information about house and market characteristics. Beggs and Graddy (2009) demonstrates a strong anchoring effect in art auctions, after ruling out the vicarious learning effect via a creative empirical design. More recently, Malhotra et al. (2015) find that in corporate acquisition processes, acquisition premium in the stock market is clearly anchored on the premium of preceding acquisitions in the same segment.

Based on these, we conjecture that patent valuation may be also subject to the anchoring effect. Valuating patents is uncertain, because of the inherent unpredictability. Although the technological functions of a patent are largely observable once being approved, its economic value remains unclear. Economic value is not only related to their technological attributes, but also dependent on a broad range of social and market factors. First, patent value is contingent on the competition from alternative technologies (Podolny and Stuart, 1995), such that market audiences will have to consider competing technologies in valuing a patent. This can be challenging when the number of alternatives is large. More importantly, technological superiority does not guarantee commercial success. Path dependence, for instance, may enable suboptimal technologies (e.g., QWERTY) to dominate the market (Vergne, 2013). Second, technological regimes also determine how much value firms may capture from patents (Malerba and Orsenigo, 1993). When appropriability is low, for instance, a firm's ability to capture patent profits will be constrained. Furthermore, realizing patent value requires complementary assets (e.g., manufacturing, distribution, and complementary technologies), which may or may not be in place (Arora et al., 2023; Teece, 1986).

These contingencies suggest that it is not sufficient for market audiences to consider only observable patent and firm characteristics in valuating patents (Gambardella et al., 2008). We posit that the ambiguity in determining the value of patents leaves audiences susceptible to anchoring based on the value of preceding patents. Due to considerable uncertainty in pricing patents, a heuristic process of anchoring-adjustment may be activated, explicitly or implicitly, in the cognitive judgement of market audiences (Bikhchandani et al., 1998; Tversky and Kahneman, 1974). Specifically, in pricing a new patent, they may first attend to the valuations of prior patents in the same domain as a salient anchor and then make adjustments, which helps simplify the complex task of patent valuation to easier operations (Malhotra et al., 2015). However, such adjustment is usually insufficient (Beggs and Graddy, 2009), so that focal patent value end up being shaped by prior patents, beyond its own inherent characteristics.

Prior patents can act as useful anchors also because of information cascades (Rao et al., 2001). When people make uncertain judgements or decisions sequentially, they tend to observe how comparable situations are handled previously by others and act upon learning from it (Bikhchandani et al., 1998). This can provide social proof for their decision-makings. If so, audiences may be prone to anchoring on the value of prior patents when valuating a patent in the same domain, which is often perceived as appropriate given the proximity and similarity between them (Malhotra et al., 2015). Towards this end, they may even look for ways to confirm that the current valuation task is similar to preceding patents, selectively attending to its information that is consistent with them, which is known as confirmatory search or selective accessibility in the anchoring process (Furnham and Boo, 2011). In sum, we expect that an anchoring effect in the stock market valuation of patents, such that patent valuation is pulled towards preceding patent value.

Hypothesis 1. Preceding patent value in the market acts as an anchor for focal patent valuation.

While we highlight anchoring as a potential mechanism for patent valuation, several issues merit attention. First, we do not consider anchoring as the only valuation mechanism. As reviewed earlier, we believe that audiences will also take into account many other relevant factors such as technological competition, market potentials, and complementary assets (Arora et al., 2023; Podolny and Stuart, 1995; Teece, 1986). However, even for these factors, which appear to be objective, audiences may still be unable to make undisputable assessment (e.g., how large the market is). This also leaves room for subjective interpretation and hence the anchoring effect. Second, patent valuation is often done by groups or teams (e.g., analysts, or investors, and lawyers) rather than individuals. While prior literature mostly analyzes anchoring in individual decision-makings, recent studies show that group decision-making is also vulnerable to anchoring bias (de Wilde et al., 2018). It is particularly so when judgmental aspects are involved (e.g., during price valuations). Indeed, Meub and Proeger (2018) show that groups are equally biased toward anchors as individuals in a price valuation task. Finally, the anchoring effect in patent valuation is not unconditional, but will be contingent on various scope conditions. To further enrich our understanding, we explore below some potential contingencies at the patent, anchor, and firm levels.

2.2. Anchoring effect and scope conditions

Patent novelty. First, we contend that anchoring may be moderated by patent novelty. Patents vary in their novelty, the extent to which a patent is distant from other patents in the same market (Arts et al., 2018). It is a key attribute of patents, as patent novelty is closely related to economic value that can be obtained, all else being equal (Fleming et al., 2007; Kaplan and Vakili, 2015). We argue that novelty may weaken the anchoring effect. Prior work on selective accessibility suggests that anchors become more plausible when preceding and focal objects are more similar (Mussweiler, 2003). Similarity will increase audiences' attendance to the shared features of them, driving audiences to underscore information that compares favorably to anchors (Malhotra et al., 2015). As a result, they will rely more on preceding patents in valuating the focal patent, leading to stronger assimilation effects of anchors.

In contrast, when focal patent is novel, it is, by definition, more distinct from preceding patents. The viability and plausibility of preceding patent valuation as information cues will be reduced (Malhotra et al., 2015). This leads to stronger contract effects (Mussweiler, 2003) as audiences tend to focus more on distinctive, rather than shared, features between anchor and focal patents. Audiences will hence consider more of the unique features of focal patents into their evaluation. Accordingly, the anchoring effect will be weakened because of the lack of similarity (Sailors and Heyman, 2019).[2]

Hypothesis 2. Anchoring on preceding patent valuation will be weaker when focal patent is more novel.

[2] Certainly, patent novelty will also breed valuation uncertainty, which may drive audiences to opt for judgmental heuristics. Although we conjecture a weaker anchoring effect due to the novelty-associated dissimilarity, we do not necessarily imply that audiences will employ fewer heuristic. Instead, we suspect that audiences will likely resort more to alternative heuristic options (e.g., rule of thumb or expert opinion heuristics), whereas anchoring is just one form of heuristics. In other words, while novelty will lead audiences towards using heuristics, anchoring may not be a good option because of the lack of similarity (Mussweiler, 2003; Sailors and Heyman, 2019).

Anchors' divergence. Second, the anchoring effect may also depend on the attributes of anchors. Specifically, we consider the role of anchors' divergence. While prior studies mostly consider single-anchor scenarios (Beggs and Graddy, 2009), audiences in many situations are presented with multiple anchors simultaneously. In the patent valuation context, information on patent grants comes out every Tuesday (Kogan et al., 2017), such that there are often several patents granted in the same technology domain on the Tuesday prior to the focal patent. The circumstance of multiple anchors deserves attention as they are not necessarily consistent. When preceding patents (i.e., anchors) have secured inconsistent valuations in the market, they provide very divergent information to audiences, rendering the anchors less viable as information cues (Connelly et al., 2011). As a result, audiences may choose to rely less on anchors but opt for more effortful (less heuristic) judgment or other mechanisms. In contrast, if preceding patent valuations are more convergent and consistent, their role as viable anchors will be reinforced. Audiences will be more likely to count on the anchors as a cognitive heuristic at ease.

Hypothesis 3. Anchoring on preceding patent valuation will be weaker when prior anchors are more divergent.

Firm's patenting frequency. Finally, the anchoring effect may also vary for different firms. Specifically, we focus on firms' patenting frequency, the number of patents a firm is granted in a given period of time (Dahlstrand, 1997). Firms differ in their patenting frequency: while some firms constantly have a large number of patents being granted, others may create only a few patents throughout their whole life cycles (Arora et al., 2023). Such differences may be determined by idiosyncratic regimes of industries and/or innovation strategies of firms (Malerba and Orsenigo, 1993).

Regardless of the underlying reasons, we suspect that patenting frequency may enhance the anchoring effect. It is more challenging to valuate patents from firms with high frequencies, as market audiences will have to spend their limited time and effort to a greater number of patents. Such capacity constraints may prompt audiences to rely on anchors (Epley, 2004; Malhotra et al., 2015), which is simpler and faster. In contrast, when a firm has a low frequency of patenting, audiences are able to allocate more time and resources to examine each of its patents in detail. This allows them to pay closer attention to patents' idiosyncratic attributes, consider more anchor-inconsistent information, and make more sufficient adjustment from anchors, which ultimately weakens the effect of anchoring.

Moreover, when a firm maintains a high patenting frequency, it constantly offers a great number of information cues in the market. As such, anchoring can serve as a more reliable and plausible mechanism for the valuation of patents granted to these firms. This might in turn propel audiences to reply more on the anchoring mechanism as their heuristics for patent valuation. Based on these, we expect.

Hypothesis 4. Anchoring on preceding patent valuation will be stronger when focal firm has a higher frequency of patenting.

3. Empirics

3.1. Data sources

To test our hypotheses on anchoring effects in patent valuation, we compile data from different sources. First, we utilize data on patent value developed by Kogan et al. (2017). In their work, Kogan et al. (2017) introduce a new measure of patent valuation in millions of US dollars, by examining abnormal stock market returns that are attributed to news about patent grants. These data (i.e., KPSS) have been made publicly available, and widely used by scholars to infer patents' private economic value (Arora et al., 2023; Hsu et al., 2021). As this measure is based on stock market trades, it is limited to patents issued to the listed U.S. firms.

Second, we gather general patent information from PatentsView. PatentsView is a platform that focuses on patent data, with the support from the U.S. Patent & Trademark Office (USPTO). It contains most observable features of patents, including patent identification, application and grant information, backward citations, technological claims, un-ambiguated inventors, assignees, location, and technology classes. As a result, PatentsView has become one of the most commonly used sources for patent attributes (Khanna, 2023; Singh et al., 2021)

Third, we also collect data on patent similarity from the Patent Text Dataverse of Harvard Dataverse, which is developed by Arts et al. (2018). They use text matching to measure the technological similarity between patents, which performs much better than the traditional measures based on various patent classification systems. We merge data from the three main different sources via unique patent number. After removing observations with substantial missing values, our main sample includes 1,054,370 patents developed by 4362 firms, between 1991 and 2010.[3]

3.2. Variables and measures

Patent value. We measure the economic value of patents by using the estimate developed in the KPSS dataset (i.e., item *xi_nominal*). This variable calculates the three-days stock market responses to the announcement that a new patent has been granted to a firm, excluding the noisy stock returns that are unrelated to the patent grant event (See more technical details in Kogan et al. (2017: 671–681). Specifically, on a patent issue date (commonly Tuesday), the market receives the information that a patent application has been approved, which will trigger stock market reaction to incorporate the patent's value into firm valuation. To estimate the patent's value, Kogan et al. (2017) first calculate the firm's abnormal market returns around the issue date, and then rule out stock price movements for reasons unrelated to the patent announcement. It is hence a good indicator of how the stock market valuates a given patent at the time of approval (Arora et al., 2023; Hsu et al., 2021). To reduce the skewness of its distribution, we take the natural logarithm of one plus the raw patent value (Higham et al., 2021).

Anchoring effect. Following the established methodology in the economics literature (Beggs and Graddy, 2009; Genesove and Mayer, 2001), we employ a hedonic regression approach (with conventional linear regression specifications) to tease out the anchoring effect. This approach breaks down the overall value into several distinct components based on linear regressions. Specifically, we first run the following regression to generate the predicted economic value of a focal patent p:

$$\pi_p = X_t\beta_p + \delta_p \tag{1}$$

where π_p is the predicted economic value of Patent p according to its observable characteristics X_t (e.g., backwards citations, claims, and inventors, as will be explained below). Then following prior research (Malhotra et al., 2015), we estimate the following equation:

$$V_p = \mu\pi_p + \lambda\underbrace{\left(V_{p-1} - \pi_p\right)}_{Anchoring} + \xi\underbrace{\left(V_{p-1} - \pi_{p-1}\right)}_{Vicarious\ learning} + \varepsilon_p \tag{2}$$

where V_p denotes the actual economic value of patent p according to

[3] The KPSS data cover patents from 1926 to 2020, PatentsView covers patents from 1976 to 2021, and Arts et al. (2018)'s similarity dataset spans from 1976 to 2013. As such, our maximum time range is between 1976 and 2013. In this paper, we choose to focus only on patents granted from 1991 to 2010, for the sake of computational capacity. Nonetheless, since we include time fixed-effects in all estimations, it is unlikely that our results are biased by the choice of time window. Moreover, we also collect data about firms' financial information from Compustat (e.g., R&D expenditures) and data about investment analysts from the Institutional Brokers Estimates System (I/B/E/S). We match them with patent data via company identifiers PERMCO and CUSIP.

KPSS (*patent value*), π_p denotes the predicted value of patent p from the hedonic Equation (1) (*predicted value of focal patent*), and the subscript *p-1* denotes prior patent(s) granted right before patent p in the same CPC technology class.[4] As USPTO normally announces patent approvals every Tuesday (Kogan et al., 2017), prior patent(s) typically refers to the one(s) granted one week before the focal patent.

$V_{p-1} - \pi_{p-1}$ is used to capture the effect of *vicarious learning*, as it reflects the extent to which the actual value of prior patent(s) exceeds their predicted value. This item is useful to rule out the overall valuation patterns in the market, as it carries information related to the preceding valuation premium or decline that might be observed (by market audiences) but not captured by factors in our estimation. For instance, there might be a temporal market trend towards over-valuating patents in a class, which results in the prior patent's valuation (V_{p-1}) being much higher than what its characteristics would typically indicate based on yearly estimations (π_{p-1}). Therefore, incorporating $V_{p-1} - \pi_{p-1}$ is useful to account for this.[5]

Finally, the *anchoring effect* is captured by the deviation item $V_{p-1} - \pi_p$. The estimate of this item within Equation (2) reflects how the value of prior patent(s) affects the valuation of focal patent p, after ruling out the effect of focal patent p's observable characteristics (Malhotra et al., 2015). Such operationalization helps identify anchoring from other confounding effects (Beggs and Graddy, 2009). A positive estimate of λ would imply that, if the predicted value of the focal patent is lower than the observed valuations of preceding patent(s) ($V_{p-1} - \pi_p > 0$), it will pull the focal valuation upwards; and vice versa. Appendix B illustrates the operationalization using examples of four patents from our sample.

Firm's patenting frequency. It indicates how frequent a firm receives patent grants from USPTO (Dahlstrand, 1997). We count the number of patents that are granted to a firm in the past three years, and use its natural logarithm value to reduce skewness. In additional analyses not tabulated here, we also use alternative moving windows (e.g., five years) and find consistent results.

Anchors' divergence. In most of the cases, there are two or more patents granted simultaneously before a focal patent in the same class, whose values can all act as anchors. We calculate anchors' divergence as the standard deviation of all anchors (i.e., $V_{p-1} - \pi_p$) for the focal patent, and use its natural logarithm in regressions to reduce skewness. Because this variable is not applicable for patents with only one single anchor, our estimation is hence limited to patents with at least two preceding patents.

Patent novelty. To capture how novel a patent is compared to others, we adopt the text-based measure developed by Arts et al. (2018). Specifically, they concatenate the title and abstract of each patent, and filter out a collection of their unique keywords representing their core technical contents. The Jaccard similarity is then calculated between any pair of patents based on their unique keywords and identify for each patent the closest patent filed in the same year. We therefore calculate patent novelty as the opposite of the highest Jaccard similarity score that each patent shares with any other patents. According to this measure, when a patent has a high similarity with others in technical contents, it is considered as less novel.

Patent characteristics. Following prior studies (Gambardella et al., 2008; Harhoff et al., 2003; Higham et al., 2021), we measure a set of key patent characteristics to be used in the hedonic Equation (1). First, we include a set of citation-related variables. *Backwards citations to foreign patents* is added as the number of citations in a patent that are made towards non-USPTO patents, which has been found to affect patents' economic value (Higham et al., 2021). For citations to US patents, we distinguish between citations added by applicants and examiners (Righi and Simcoe, 2019), by using two variables *backwards citations to US patens by applicants* and *backwards citations to US patens by examiners*.[6] *Backwards non-patent citations* refers to the number of cited references in a patent that are non-patent documents (e.g., scientific literature or juridical terms). *Number of claims* counts the total number of technological claims in a patent that defines the scope and complexity of an invention for which patent protection applies (Gruber et al., 2013).

We also add *number of CPC classes* by counting the total number of three-digit CPC classes under which a patent has been classified. It reflects a patent's technological breadth or generality. Grant *lag* is introduced by measuring the number of days between the application data and the grant date of a patent (Harhoff and Wagner, 2009). *Inventor team's size* counts the number of inventors for a patent; *inventor team's experience* calculates the mean of team members' patenting experience (e.g., the number of patents granted to them) prior to a focal patent. Finally, to account for heterogeneity across time, technology domains, and firms, we incorporate both firm fixed-effects and CPC class × year fixed-effects.

Table 1 reports descriptive statistics for these key variables. It seems surprising that the univariate correlation between *patent value* and *anchoring effect* is negative. However, the pairwise negative correlation is in fact mechanical, since the measure of anchoring effect includes a negative term of the predicted patent value in Equation (2). To understand the actual anchoring effect, it is therefore necessary to include all of three items simultaneously on the right side of Equation (2), as their univariate effects may not be very meaningful (Beggs and Graddy, 2009; Malhotra et al., 2015).

3.3. Estimation approach

We employ a fixed-effects estimation approach that help account for heterogeneity across technology classes and firms. Specifically, by incorporating CPC class × year fixed-effects, our estimation absorbs heterogeneity across technology class within each year (e.g., class size and technology fertility) that may affect patent value (Dass et al., 2017). We also add firm fixed-effects, which helps rule out firm-level heterogeneity (Kogan et al., 2017). This is important because stock market responses to patent announcements can be largely dependent on assignee firms' characteristics. To account for patent nonindependence and heteroskedasticity, we cluster standard errors by firms (Alcácer et al., 2009; Gambardella et al., 2008). We incorporate these specifications by using *reghdfe* in Stata that performs well with a large dataset and high-dimensional fixed-effects (Correia, 2016).

3.4. Main results

Table 2 presents the hedonic regression results according to Equation (1). In line with most of prior studies, we find that patent value is positively associated with, for instance, novelty, number of classes, and backwards citations to foreign patents. Based on this estimate, we generate the three key variables to be used Equation (2): *anchoring effect* ($V_{p-1} - \pi_p$), *vicarious learning* ($V_{p-1} - \pi_{p-1}$), and *predicted value of focal patent* (π_p).

Table 3 reports the results for the anchoring effect. In Model 2, we see a significant and positive effect of anchoring effect on patent value

[4] When there are two or more prior patents granted at the same time, we use their mean value to capture V_{p-1} and $V_{p-1} - \pi_{p-1}$.

[5] To further check the robustness of our results, we create a variable, *market trend*, by measuring the average valuations of all other patents issued on the same date and in the same class as the focal patent. It helps account for market trend that is closer to the valuation of the focal patent. The results, after controlling market trend, are reported in Appendix A. In another analysis not reported here, where we remove the item $V_{p-1} - \pi_{p-1}$, the results stay consistent.

[6] In PatentsView, citations added by examiners are only identified from 2002. So *backwards citations to US patents by examiners* is set zero for all observations before 2002. This will not bias our estimation as we include year fixed effects in our estimations. Nonetheless, we run a set of analyses that use only patents from 2002 onwards and find highly consistent results.

Table 1
Descriptive statistics.

	Variables	N	Mean	S.D.	Min.	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Patent value	10,54,370	2.04	1.51	0.00	8.72															
2	Patent novelty	10,54,370	−0.27	0.21	−1.00	−0.05	−0.06														
3	Inventor team's size	10,54,370	2.68	1.85	1.00	76.00	0.02	−0.10													
4	Inventor team's experience	10,54,370	16.44	41.59	0.00	2507.00	−0.11	−0.10	−0.01												
5	Number of CPC classes	10,54,370	1.60	0.87	1.00	14.00	0.02	−0.07	0.10	0.02											
6	Patent gant lag	10,54,370	1006.09	538.62	−73.00	21477.00	0.03	0.04	0.05	−0.01	−0.03										
7	Backwards citations to foreign patents	10,54,370	3.02	8.60	0.00	452.00	−0.02	−0.11	0.12	0.07	0.10	0.10									
8	Backwards citations to US patents by applicants	10,54,370	11.26	28.12	0.00	1540.00	0.11	−0.11	0.07	0.07	0.08	0.04	0.53								
9	Backwards citations to US patents by examiners	10,54,370	3.04	4.76	0.00	306.00	−0.02	0.03	0.00	0.02	−0.03	0.34	0.03	0.00							
10	Number of claims	10,54,370	17.79	13.48	1.00	683.00	0.13	−0.02	0.06	0.03	0.01	0.13	0.06	0.12	0.08						
11	Backwards non-patent citations	10,54,370	4.10	16.51	0.00	2823.00	0.08	−0.14	0.08	0.06	0.10	0.13	0.38	0.42	0.01	0.10					
12	Achoring effect	10,06,638	0.01	1.35	−6.72	6.57	−0.81	0.03	0.00	0.09	0.00	0.00	0.05	−0.08	−0.02	−0.12	−0.04				
13	Vicarious learning	10,06,638	0.01	0.20	−2.17	4.21	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.14			
14	Predicted value of focal patent	10,06,638	2.05	1.41	−0.96	8.24	0.93	−0.06	0.02	−0.12	0.02	0.03	−0.03	0.12	−0.02	0.14	0.09	−0.87	0.01		
15	Anchors' divergence	9,64,974	3.40	0.97	0.00	7.41	0.25	−0.05	0.04	−0.04	−0.04	0.15	0.02	0.03	−0.05	0.07	0.09	0.07	0.23	0.26	
16	Firm's patenting frequency	10,06,638	6.75	2.04	0.00	9.67	−0.17	0.02	0.03	0.12	−0.07	0.10	−0.03	−0.13	0.10	−0.09	−0.11	0.09	0.00	−0.17	−0.06

Table 2
Hedonic regressions.

VARIABLES	Model 1
Patent novelty	0.029[b]
	(0.009)
Inventor team's size	−0.001
	(0.001)
Inventor team's experience	−0.000[d]
	(0.000)
Number of CPC classes	0.006[a]
	(0.002)
Patent gant lag	0.000
	(0.000)
Backwards citations to foreign patents	0.001[c]
	(0.000)
Backwards citations to US patents by applicants	−0.000
	(0.000)
Backwards citations to US patents by examiners	−0.001[b]
	(0.000)
Number of claims	0.000
	(0.000)
Backwards non-patent citations	−0.000
	(0.000)
Constant	2.047[a]
	(0.014)
Firm FE	Yes
CPC class × Year FEs	Yes
Observations	1,054,370
R-squared	0.868

Robust standard errors in parentheses.
[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.
[d] $p < 0.10$.

($\beta = 0.006$; s.e. $= 0.002$). Fig. 1 presents binned scatterplots for the relation between anchoring effect and patent value. We see that the relation is mostly increasing, with the possible exception of patents that experience very low-value anchors. To better understand the magnitude of its effect, we perform general dominance statistics (Sime et al., 2023) by comparing the relative importance of anchoring effect against other

Table 3
Fixed-effects estimation of anchoring effect.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Achoring effect		0.006[b]	0.006[b]	−0.021[a]	0.026[b]	−0.003
		(0.002)	(0.002)	(0.004)	(0.008)	(0.010)
Patent novelty			−0.004			−0.002
			(0.014)			(0.012)
Achoring effect × Patent novelty			−0.014[c]			−0.015[b]
			(0.006)			(0.005)
Anchors' divergence				−0.005		−0.006
				(0.008)		(0.008)
Achoring effect × Anchors' divergence				−0.070[a]		−0.071[a]
				(0.006)		(0.006)
Firm's patenting frequency					−0.097[a]	−0.098[a]
					(0.027)	(0.026)
Achoring effect × Firm's patenting frequency					0.038[a]	0.045[a]
					(0.010)	(0.010)
Vicarious learning	0.264[a]	0.258[a]	0.258[a]	0.362[a]	0.251[a]	0.355[a]
	(0.024)	(0.024)	(0.024)	(0.027)	(0.023)	(0.025)
Predicted value of focal patent	0.975[b]	0.980[b]	0.990[b]	0.976[b]	0.908[b]	0.897[b]
	(0.309)	(0.310)	(0.360)	(0.316)	(0.281)	(0.331)
Constant	0.049	0.037	0.018	0.052	0.176	0.203
	(0.633)	(0.633)	(0.737)	(0.646)	(0.575)	(0.676)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
CPC class × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,006,515	1,006,515	1,006,515	964,628	1,006,515	964,628
R-squared	0.869	0.869	0.869	0.873	0.872	0.876

Robust standard errors in parentheses.
[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.

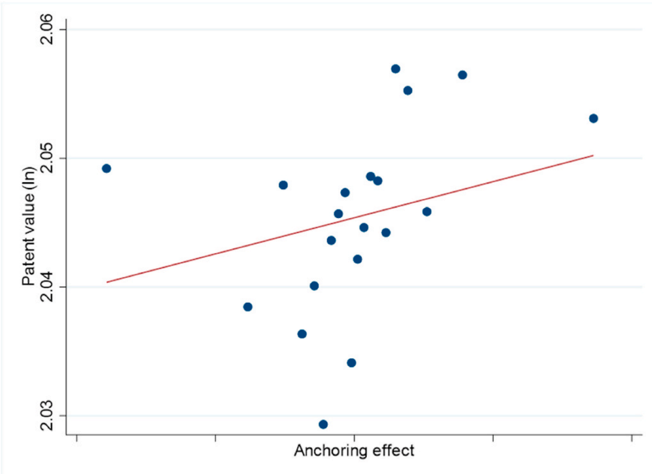


Fig. 1. Binned scatterplots of anchoring and patent value.

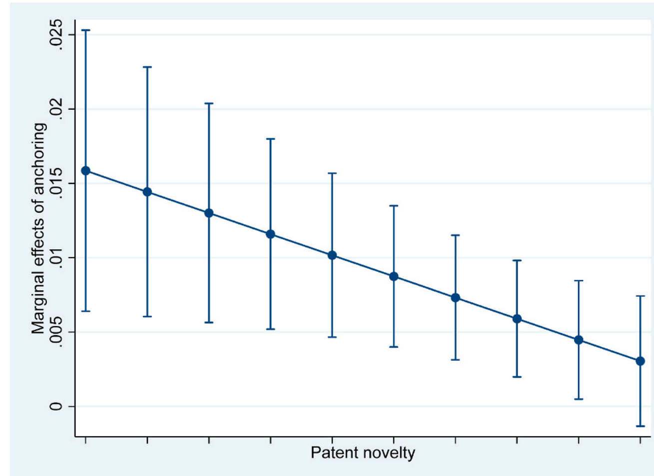


Fig. 2. Marginal effects of anchoring on novelty.

Table 4
Dominance analysis.

Variables	Dominance statistics (1)	Dominance statistics (2)
Forward citations		0.0081
Predicted value of focal patent	0.3633	0.3606
Anchoring effect	0.2511	0.2490
CPC class effect	0.0356	0.0351
Firm effect	0.3288	0.3264
Year effect	0.0212	0.0209

variables using Stata command *domin* (Luchman, 2021). Results in Table 4 suggest that firm-level fixed-effects and the predicted value play the most dominant role (d = 0.3288 and 0.3633, respectively). This is intuitive since stock market returns are known for being contingent on firm characteristics (e.g., size or reputation) and inherent quality of patents. However, the anchoring effect size (d = 0.2511) is also substantive as it appears much larger than the impacts of year (d = 0.0212) and technology class (d = 0.0356). Altogether, those findings support our core claim: Preceding patents acts an important anchor for market audiences in valuing a focal patent (**Hypothesis 1**).[7]

In Model 3 of Table 3, we include the interaction term between (mean-centered) anchoring effect and patent novelty. It shows a negative and significant effect on patent value (β = −0.014; s.e. = 0.006). Fig. 2 depicts that the marginal effect of anchoring decreases as patent novelty increases. Specifically, when a patent's novelty is at the first quartile, anchoring effect is 0.0058 (z = 2.90); when novelty is at the third quartile, anchoring effect is decreased to 0.0043 (z = 2.10), by about 25.8%. This pattern is consistent with our **Hypothesis 2** that anchoring on preceding patent valuation will be weaker when focal patents are more novel.

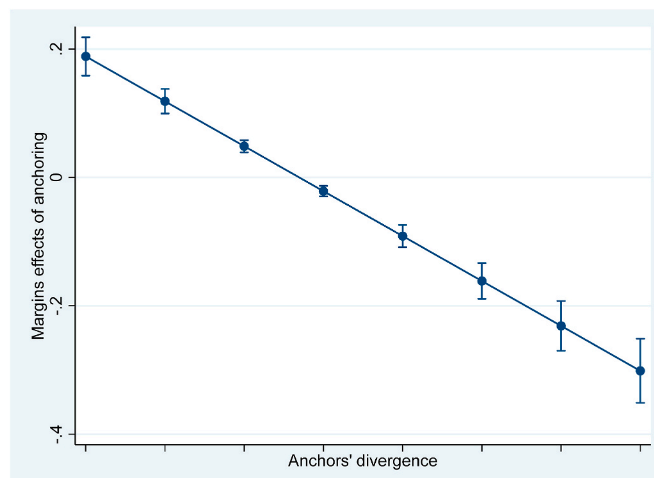


Fig. 3. Marginal effects of anchoring on anchors' divergence.

In Model 4, we add the interaction term between anchoring effect and anchors' divergence. It has a negative and significant effect on patent value (β = −0.070; s.e. = 0.006).[8] Fig. 3 shows that the marginal effect of anchoring decreases as anchors' divergence increases. Specifically, when prior anchors' divergence is at the first quartile, the anchoring effect size is 0.026 (z = 6.75); when the divergence is at the third quartile, the anchoring effect turns to negative (−0.067; z = −9.61). This is consistent with our **Hypothesis 3** that anchoring on preceding patent valuation will be reduced when prior anchors are more divergent.

It is a bit surprising that anchoring effect is negative on the right end when prior anchors are more divergent. This indicates reverse anchoring, rather than a simply weaker anchoring effect: when facing very divergent signals, audiences tend to form their valuation deviating from prior average valuation. This, however, is not totally unreasonable.

[7] It is worth noting that the change of R-squared from Model 1 to Model 2 is very small, which seems to suggest that anchoring effect makes limited additional contributions. However, it does not necessarily mean that anchoring effect itself has little prediction power. Dominance statistics are more informative for interpreting its relative importance, which reflect the contributions of anchoring effect when combined with each of the other variables (i.e., examining all possible combinations of included and excluded anchoring effect).

[8] It is worth noting that the coefficient of anchoring effect turns negative in Model 4. This does not mean that the main effect of anchoring is negative from this estimation. Coefficients of constitutive elements in models with interaction terms are not unconditional or main effects. Instead, they indicate the effects of constitutive elements under a limited condition (the condition that the moderating variable equals zero) (Brambor et al., 2006). A such, we refer to Model 2 for its unconditional main effect.

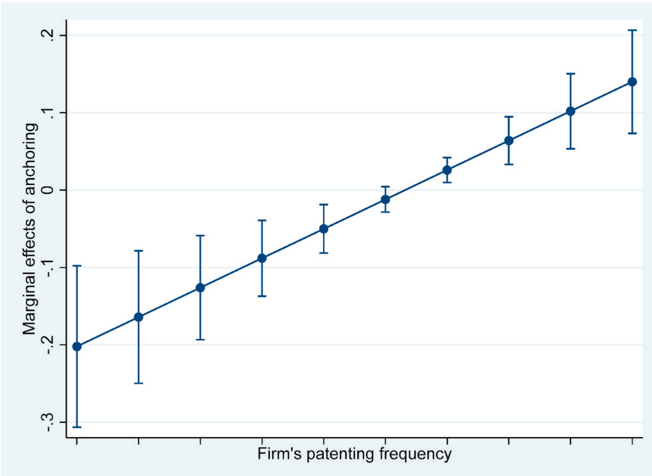


Fig. 4. Marginal effects of anchoring on patenting frequency.

One possible explanation is that prior valuation divergence drives audiences to shift away from average value to extreme values. Suppose there are two prior patents with different valuations, 1 and 10 (in million USD), respectively. The average valuation is hence 5.5. Because of such big divergence, audiences may not regard 5.5 as a reliable signal to use. Instead of using the average, they may anchor valuation around one of prior valuations (1 or 10) given their interpretation. If so, their reference point will mechanically deviate from the average valuation, which is used to operationalize our anchoring effect, resulting in the observed reverse-anchoring effect. The wider the gap between prior valuations, the greater the deviation from the average tends to be. As this is purely our conjecture, more dedicated work is needed to investigate it. Nevertheless, it seems safer to conclude from Model 4 that anchoring effect is more profound when divergence is small.

In Model 5, we include the interaction term between anchoring effect and firm's patenting frequency. Its effect is significant and positive on patent value (β = 0.038; s.e. = 0.010). Fig. 4 shows that the marginal effect of anchoring increases as firm's patenting frequency increases. Specifically, when patenting frequency is at the first quartile, the anchoring effect size is marginally negative (−0.014; z = −1.64); when frequency is at the third quartile, the anchoring effect turns to become significantly positive (0.086; z = 4.11). Our **Hypothesis 4** is hence supported that anchoring on preceding patent valuation is stronger when focal firms have a higher patenting frequency. However, it is worth noting that anchoring effect is significantly negative at the lower end of firms' patenting frequency (at about 20th percentile). One possible reason could be that when firms create minimal patents in a given period, they are likely atypical innovators compared to conventional peers who are constantly patenting in the market. In valuating patents from such type of atypical firms, market audiences may tend to deviate from prior anchors that are more reflective of market conventions. Anyway, these findings imply that while the main effect of anchoring is found to be positive, under certain circumstances, it can turn out to become negative.

3.5. Robustness checks and Extensions

To supplement main analysis, we conduct a set of extensional analyses that examine the robustness of our results, rule out alternative explanations, and further explore the data.

Quality heterogeneity. One may be concerned that our estimation above does not control for patents' scientific value/quality that can largely determine their economic value. Although we include a wide range of observable patent characteristics, there might still be some *omitted* and/or *unobservable* quality-related factors that influence both the anchoring effect and patent value. We are less concerned about factors that are completely unobservable in the market. For such factors, the market would show no reaction, either. In other words, factors that are entirely unobservable will have no impact on the stock market returns to patent grants (i.e., the measure of patent value). However, the existence of factors that are omitted by us but observable in the market is problematic. This is inevitable since the list of control variables can never be exhaustive.

To alleviate the concern about quality heterogeneity, we follow prior studies to use forward citations as a proxy for patents' scientific quality (Arora et al., 2023; Harhoff et al., 2003; Moser et al., 2018; Mowery and Ziedonis, 2002) and control for it in our primary estimation.[9] The results are presented in Table 5. The effect of forward citations is significantly positive, which is consistent with Kogan et al. (2017). More importantly, the estimations of our core variables stay stable after controlling for patent quality.

Moreover, to further check the potential influence of patent quality, we also use the anchoring effect item ($V_{p-1} - \pi_p$) to predict forward citations, with similar specification in Equation (2). Supposing that our findings are driven by patent quality, we should expect a significant and positive effect of anchoring on forward citations, too. However, in the additional estimation not reported here, we see a very weak association between them (β = 0.001; s.e. = 0.003). This hints that our results are less likely to be confounded by patents' scientific quality.

Matched pairs. To further account for potential concerns of unobservable heterogeneity (e.g., market potentials for commercialization), we employ a matching approach. Specifically, we match two patents filed in the same year, if they have the highest Jaccard similarity scores of their keywords (Arts et al., 2018). As a result, each pair of patents are highly similar in terms of their technological contents.[10] We then repeat our estimation with additional fixed-effects at the patent-pair level. Such specification ensures that patents within each paired cell are more comparable in other dimensions (e.g., novelty, quality, popularity, and market potentials), which helps better tease out the anchoring effect. The results are reported in Table 6, which are largely consistent with our main findings in Table 3. One noticeable difference is that the moderation effect of patent novelty turns to be non-significant. This is not surprising. After the matching process, two patents in the same pair have a very similar degree of patent novelty, such that the estimation with patent-pair fixed effects may be less efficient in identifying the effect of patent novelty.

Anchoring and 'bias'. We also explore whether the anchoring effect leads to more valuation 'bias'. By bias, we mean the extent to which a patent's economic valuation deviates from its scientific quality. As shown in Fig. 5, the univariate relation between patent value and forward citations is mostly monotonical, with some deviations. The strong, positive correlation between them is intuitive (Harhoff et al., 2003; Kogan et al., 2017), since patents' economic value should be closely related to how much scientific advancement they make.

However, it is interesting to explore the deviations between economic and scientific value (i.e., valuation bias). Specifically, we suspect that anchoring effects may contribute to the valuation bias, as anchors

[9] To ensure comparability of forward citations, we standardize them by the spell of CPC class × Age, although unstandardized measure leads to similar findings. Of course, one may question the temporal sequence between patents' economic value and forward citations. While economic value is measured at three days after a patent's grant announcement, the number of forward citations is in fact measured after more than 10 years in our sample. It seems strange to use a future indicator to predict the past. However, if assuming that a patent's inherent quality stays constant and forward citations only help unveil it, then temporal sequence is less problematic. We also use its log value to reduce skewness.

[10] Some patents may appear multiple times in the sample, as they can be the closest ones for different patents. As such, the sample size is larger than our original one.

Table 5
Quality control.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Achoring effect		0.006[b]	0.006[b]	−0.021[a]	0.026[b]	−0.003
		(0.002)	(0.002)	(0.004)	(0.008)	(0.010)
Patent novelty			−0.002			−0.000
			(0.013)			(0.012)
Achoring effect × Patent novelty			−0.015[c]			−0.015[b]
			(0.006)			(0.005)
Anchors' divergence				−0.006		−0.006
				(0.008)		(0.008)
Achoring effect × Anchors' divergence				−0.070[a]		−0.071[a]
				(0.006)		(0.006)
Firm's patenting frequency					−0.096[a]	−0.098[a]
					(0.027)	(0.026)
Achoring effect × Firm's patenting frequency					0.038[a]	0.045[a]
					(0.010)	(0.010)
Vicarious learning	0.264[a]	0.258[a]	0.258[a]	0.361[a]	0.251[a]	0.355[a]
	(0.024)	(0.024)	(0.024)	(0.027)	(0.023)	(0.025)
Predicted value of focal patent	0.954[b]	0.960[b]	0.960[b]	0.956[b]	0.891[b]	0.874[b]
	(0.300)	(0.300)	(0.347)	(0.306)	(0.274)	(0.321)
Forward citations (patent quality)	**0.016**[a]	**0.016**[a]	**0.016**[a]	**0.016**[a]	**0.014**[a]	**0.013**[a]
	(0.003)	**(0.003)**	**(0.003)**	**(0.003)**	**(0.002)**	**(0.002)**
Constant	0.091	0.080	0.079	0.091	0.211	0.250
	(0.613)	(0.613)	(0.710)	(0.626)	(0.560)	(0.657)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
CPC class × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,006,515	1,006,515	1,006,515	964,628	1,006,515	964,628
R-squared	0.869	0.869	0.869	0.873	0.872	0.876

Robust standard errors in parentheses.
[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.

Table 6
Estimation from matched pairs.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Achoring effect	0.006[b]	0.005[b]	−0.006[b]	0.015[a]	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Patent novelty		0.000			0.001
		(0.006)			(0.006)
Achoring effect × Patent novelty		−0.004			−0.006
		(0.004)			(0.004)
Anchors' divergence			−0.004[b]		−0.004[b]
			(0.001)		(0.001)
Achoring effect × Anchors' divergence			−0.055[a]		−0.056[a]
			(0.001)		(0.001)
Firm's patenting frequency				−0.077[a]	−0.078[a]
				(0.002)	(0.002)
Achoring effect × Firm's patenting frequency				0.029[a]	0.034[a]
				(0.001)	(0.001)
Vicarious learning	0.286[a]	0.286[a]	0.372[a]	0.281[a]	0.367[a]
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Predicted value of focal patent	0.937[a]	0.937[a]	0.950[a]	0.926[a]	0.937[a]
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.126[a]	0.126[a]	0.103[a]	0.153[a]	0.132[a]
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Matched pair FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Firm FE	Yes	Yes	Yes	Yes	Yes
CPC class	Yes	Yes	Yes	Yes	Yes
Observations	1,236,168	1,236,168	1,163,318	1,236,168	1,163,318
R-squared	0.952	0.952	0.953	0.953	0.954

Robust standard errors in parentheses.
[a] $p < 0.001$.
[b] $p < 0.01$.

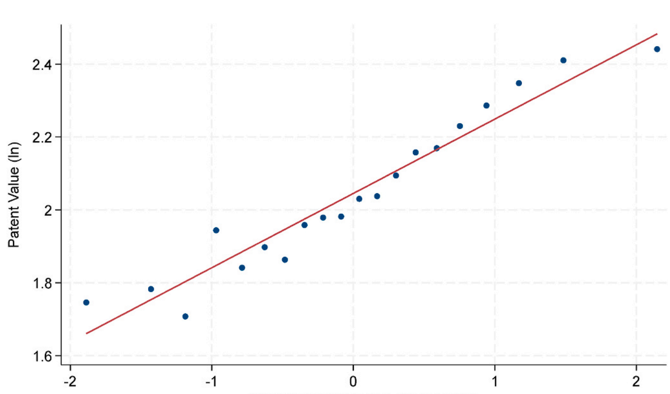


Fig. 5. Binned scatterplots of patent value and citations.

pull a patent's valuation away from its inherent characteristics. To examine this possibility, we first use the number of forward citations that a patent receives (as a proxy for patents' inherent scientific quality)

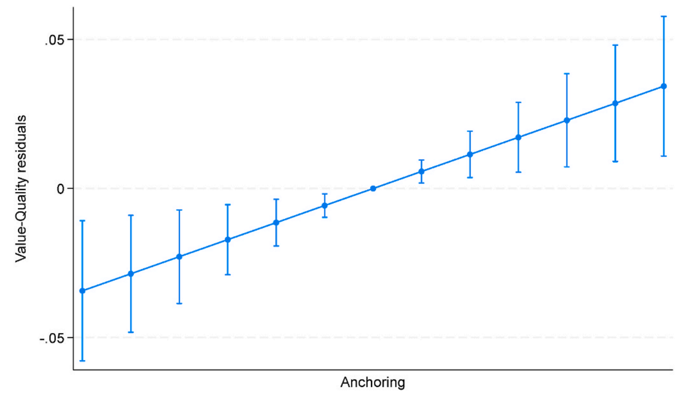


Fig. 6. Marginal effects of anchoring on residuals.

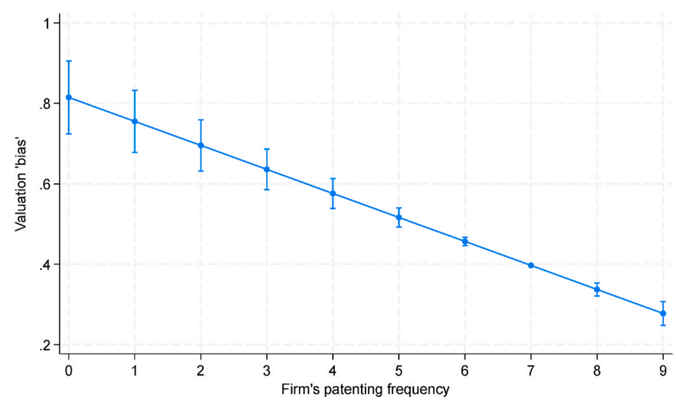
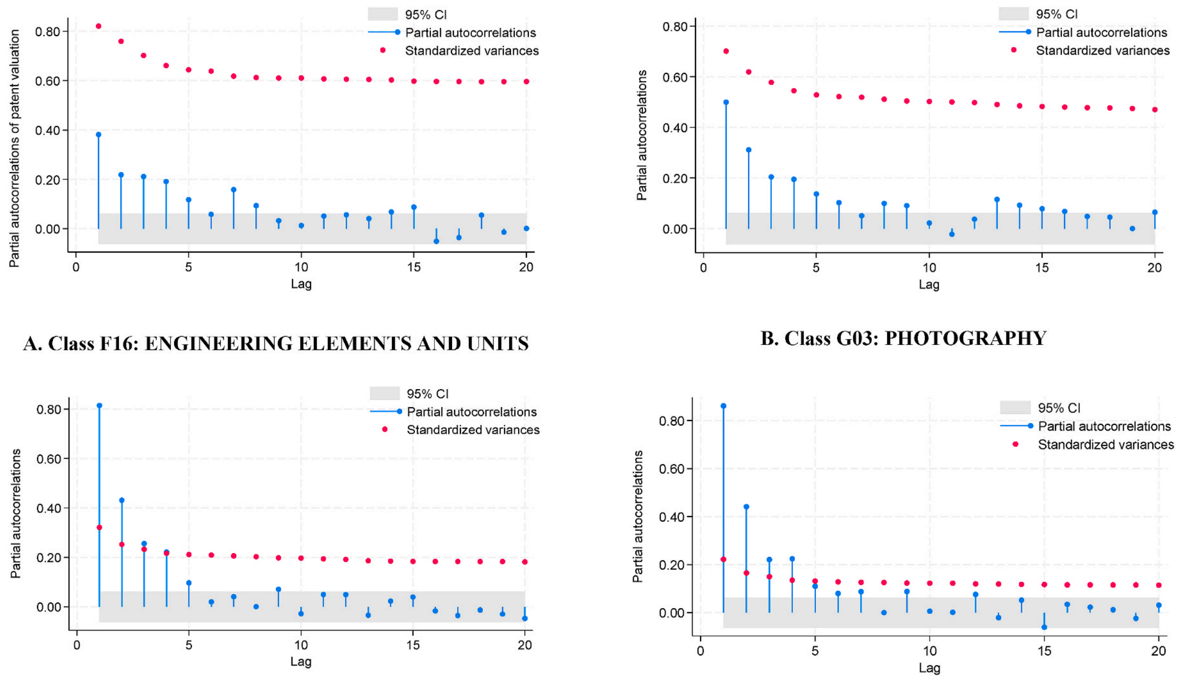


Fig. 7. Patenting frequency and valuation bias.

to estimate its economic value. Based on that, we generate the predicted residuals, which are used to indicate valuation bias. Negative residuals indicate that patents are undervalued given their quality, whereas positive residuals suggest overvaluation. We then use the *anchoring effect* term from Equation (2) to estimate the residuals. The results are summarized in Fig. 6. We find that when anchors are at the high end, they will pull a patent's economic value substantially over its scientific quality (i.e., overvaluation). In contrast, low-value anchors can drag down patents' economic value, relative to their quality (i.e., undervaluation). Altogether, these findings hint that the anchoring effect is an important factor that set a patent's economic valuation apart from its scientific quality.

A follow-up inquiry could then delve to the circumstances under which such valuation 'bias' can be alleviated. Although it falls beyond the scope of this paper, our theoretical framework offers some hints. Specifically, we maintain (in Hypothesis 4) that for firms with frequent patenting, anchoring could be a more reliable mechanism for patent valuation. If this is the case, we shall see that patenting frequency will help decrease valuation bias. To test it, we use the absolute value of the predicted residuals above as an indicator of valuation bias, and then employ patenting frequency to estimate it. The results are depicted in Fig. 7. Consistent with our conjecture, it suggests that for firms with greater patenting frequency, the absolute deviation between patent's economic and scientific value decreases.

Anchoring and autocorrelation. While our test of the anchoring effect focuses only on the information disclosed in the previous period, this process may not necessarily be strictly Markov. That is because market audiences may also refer to the information from earlier periods. But even so, it is still reasonable to assume that they would pay greater attention to recent valuation information than historical data (Malhotra et al., 2015), which motivates us to employ the most recent patent



A. Class F16: ENGINEERING ELEMENTS AND UNITS

B. Class G03: PHOTOGRAPHY

C. Class H01: ELECTRIC ELEMENTS

D. Class H04: ELECTRIC COMMUNICATION TECHNIQUE

Fig. 8. Partial autocorrelation in four exemplar classes.

valuation in our main analyses.

Nonetheless, our anchoring claims would have two implications: 1) there is a strong form of serial autocorrelation of patent valuation across different period lags; 2) autocorrelation decreases for deeper lags. To verify this, we plot in Fig. 8 the partial autocorrelation of four of tech classes with the highest number of periods. Across different classes, it seems quite consistent that while there is serial autocorrelation over multiple period lags, current patent valuation is primarily influenced by that in the first lag rather than deeper lags.

Multicollinearity and alternative measure. As we follow prior research to operationalize the anchoring effect (Beggs and Graddy, 2009), this approach generates several variables that are likely to be mechanically correlated. Indeed, as seen in Table 1, there is a high correlation between *anchoring effect* and *predicted value of focal patent*. This is not surprising given that anchoring effect is defined as a function of the latter. Still, the results might be biased by multicollinearity. To examine the robustness of our findings, we use an alternative measure. Specifically, instead of employing $V_{p-1} - \pi_p$ in Equation (2), we simply use V_{p-1} (i.e., *value of prior patents*) to measure anchoring effect, which has a relatively low correlation with *predicted value of focal patent* (r = 0.328).

We then repeat analyses using this alternative measure. The results are reported in Table 7. In line with our Hypothesis 1 on anchoring, the effect of *value of prior patents* is significantly positive on the valuation of focal patents in Model 1. We also see results supporting our Hypothesis 2 in Model 2, however, whereas Hypotheses 3 and 4 are not supported here, which is inconsistent with findings in our primary specification. As we lack a basis to assess which model specification is superior,[11] we are unable to draw a definite conclusion regarding the two Hypotheses 3 and 4. Nonetheless, as both specifications lead to support for the main effect of anchoring, we can be more confident to conclude that our core claim is supported: A patent's valuation is anchored on the value that preceding patents have secured.

4. Discussion

This paper directs attention to the way how the market valuates patents. While prior studies focus mostly on the inherent characteristics of patents and firms in explaining patent value, we emphasize the cognitive judgment process of market audiences. Specifically, building on behavioral economics, we propose the anchoring effect as an important mechanism that drives patent valuation. Our analysis of U.S. patents provides broad support, as patent valuation is found to be significantly anchored on the value that preceding patents in the same market have secured. We also find the effect is stronger when focal patents are of lower novelty, when prior anchors are more consistent, and when focal firms have a high patenting frequency. Our further analysis suggests that the anchoring effect acts as an important factor that diverges patents' economic valuation away from their scientific quality. By doing so, our research provides several important implications.

4.1. Patent value and anchoring

Prior literature has long underscored the importance of exploring the economic value of patents (Bessen, 2008; Gambardella et al., 2017; Harhoff et al., 2003; Kogan et al., 2017). While research has examined many patent and firm characteristics (Arora et al., 2023; Odasso et al., 2015), they only explain a proportion of value variance (Gambardella et al., 2008). In this study, we argue that the lack of explanatory power is due to the ignorance of market valuation mechanisms. Because patents' economic value is stemmed from how the market interprets and receives them, the cognitive mechanism employed by market audiences play a substantive role in shaping patent valuation (Rindova and Petkova,

[11] While the alternative measure (i.e., V_{p-1} or *value of prior patents*) reduces concerns about multicollinearity, our primary measure (i.e., $V_{p-1} - \pi_p$) draws closely on the prior theoretical foundation (Malhotra et al., 2015). Nonetheless, in our view, the latter is still the preferred specification, because some scholars indicate that multicollinearity might not be a big econometric problem as it does not introduce much bias (Lindner et al., 2020).

Table 7
Alternative measures of anchoring.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Value of prior patents	0.006[b]	0.006[b]	0.014[a]	0.009[d]	0.018[a]
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Patent novelty		0.068[c]			0.071[c]
		(0.033)			(0.035)
Value of prior patents × Patent novelty		−0.032[c]			−0.034[c]
		(0.015)			(0.017)
Anchors' divergence			−0.017[a]		−0.018[a]
			(0.004)		(0.004)
Value of prior patents × Anchors' divergence			0.007[a]		0.008[a]
			(0.002)		(0.002)
Firm's patenting frequency				−0.099[b]	−0.100[b]
				(0.034)	(0.036)
Value of prior patents × Firm's patenting frequency				0.005	0.006
				(0.008)	(0.010)
Vicarious learning	0.258[a]	0.258[a]	0.306[a]	0.259[a]	0.307[a]
	(0.024)	(0.024)	(0.027)	(0.023)	(0.025)
Predicted value of focal patent	0.975[b]	0.979[b]	0.957[b]	0.913[b]	0.912[b]
	(0.309)	(0.357)	(0.313)	(0.292)	(0.345)
Constant	0.037	0.028	0.053	0.158	0.141
	(0.633)	(0.731)	(0.640)	(0.599)	(0.707)
Firm FE	Yes	Yes	Yes	Yes	Yes
CPC class × Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	1,006,515	1,006,515	964,628	1,006,515	964,628
R-squared	0.869	0.869	0.870	0.871	0.871

Robust standard errors in parentheses.
[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.
[d] $p < 0.10$.

2007). Specifically, by bringing in the perspective of cognitive heuristics (Malhotra et al., 2015; Tversky and Kahneman, 1974), we argue and find evidence that patent valuation is subject to the anchoring effect. Market audiences, consciously or unconsciously, use preceding patent value as an important heuristic to deal with uncertainty in valuating focal patent, on top of their vicarious learning.

However, the anchoring effect in patent valuation, in our view, is a weak form of anchoring. In the traditional experimental research, scholars have mostly visualized a form of strong anchoring (Furnham and Boo, 2011): focal estimates will be located closely around an anchor as adjustments are usually subtle. In our setting, while focal valuation is indeed significantly shaped by prior patents, they do not seem to cluster tightly around them. This is not very surprising, because patents differ a lot in their attributes even if they are assigned to the same technology class (Arts et al., 2018). As investors observe and incorporate these attributes in their valuation, they are likely to make substantial adjustments from prior patents' value, even though they use them as anchors. This form of weak anchoring is not unique in patent valuation, as they are evident in other market valuation processes such as corporate acquisitions (Malhotra et al., 2015).

Our empirical analysis of anchoring is enabled by the measure developed by Kogan et al. (2017), which has become widely used as a proxy for private economic value of patents (Arora et al., 2023). It estimates the short-term market reaction to news on patent grants, after isolating measurement noise. As compared to other approaches (Bessen, 2009; Hall et al., 2005; Harhoff et al., 2003), KPSS is useful to both measure how the market valuates each patent *and* examine the possible valuation association between preceding and focal patents. However, while reflecting very short-term market responses, it does not reveal how patents may be valued over longer time periods. Market valuation of patents can change over time, particularly after more information becomes available and/or market conditions change.

Because the economic value of any assets is contingent on time and space, our measure cannot reflect the universal patent value in the market. In fact, there might be no inherent patent value that stay constant at all. For instance, creative destruction from competitors may render a once valuable patent useless (Essendorfer et al., 2015); escalated demand may boost the value of certain patents (e.g., mRNA vaccines during Covid-19 pandemic). Such time-dependent nature, at least in our view, makes it barely meaningful to search for a universal measure of patent value. Rather, it is crucial to specify the timeframe (and context) within which one estimates patent value. In our study, the anchoring effect we observe is based on short-term stock reaction, which may be different from long-term valuation (Chemmanur et al., 2022). This issue applies not only to the measure by Kogan et al. (2017), but also to other patent value measures (and forward citations (Lerner and Seru, 2022)). Consider the use of patent renewal as an example (Bessen, 2008). Decisions on whether or not to renew patents can shift dramatically after superior alternative technologies emerge, suggesting also a time-dependent nature of this valuation method.

4.2. Valuation "bias"

Our findings suggest that market audiences rely on preceding patent valuations as plausible anchors in estimating patent value. Because of the anchoring effect, however, patent value is likely to become disconnected with patents' inherent characteristics. Since these characteristics predominantly (though not completely) determine patents' scientific value (Fleming, 2001; Kaplan and Vakili, 2015), the anchoring effect will hence contribute to the decoupling between patents' scientific and economic value. While they are generally correlated (Harhoff et al., 1999; Kogan et al., 2017), scientific and economic value of patents are also found to be decoupled (Bessen, 2008; Higham et al., 2021). One possible explanation is that they are different in nature, such that the same patents will naturally have different economic and scientific value (Arora et al., 2023; Higham et al., 2021).[12]

Our findings provide an important alternative explanation to the decoupling: because patent valuation is anchored on preceding patents, rather than only on a patent's characteristics, its value becomes divergent from its scientific value, thereby leading to potential valuation 'bias'. We use valuation 'bias' to indicate the extent to which economic value is deviated from scientific value. In a more efficient market, one would expect a tighter coupling between them, since a patent with high scientific value should help enhance productivity, leading to more economic value, *ceteris paribus*. However, as the anchoring process brings in a fair amount of social construction, valuation 'bias' is likely to be introduced. Supporting this, our extensional analysis shows that anchoring contributes significantly to the divergence between patents' scientific and economic value. These findings direct attention to cognitive heuristics in the valuation process to explain the valuation 'bias' in the market (or the lack of market efficiency).

4.3. Practical implications

Our findings also provide implications to practitioners in patent examination offices and patenting firms, as well as policy makers. For patent examination offices such as USPTO, it is useful to understand that the timing of patent grants matters for patents' market valuation, at least in a short run. When a patent is granted after high-value anchors, it is likely to secure a higher valuation; and vice versa. Although patent examiners and administrators may not deliberately choose the timing and sequence of patent grants, and market valuation may not be their primary concerns; it is still useful for patent offices to recognize that the timing and sequence of their patent approvals can have a considerable, unintentional impact on the market.

Firms, on the other side, may strategically design their timing of patent development and application to achieve a better valuation. Even though patent grant time is out of their control, firms could still speed up or delay patent application, trying to get approvals right after high-value anchors. However, because the anchoring effect is not unconditional, firms should also recognize the important contingencies. Specifically, our moderation tests suggest that it is more important for firms to leverage the anchoring effect, if they are developing a great number of patents per year (i.e., a high patenting frequency), and/or if the patents they develop are mostly incremental (i.e., less novel from others). In contrast, firms may find it less necessary to consider anchoring, if the market is inconsistent in valuating prior patents (i.e., a lack of anchors' consistency).

Moreover, it is also necessary for policy makers to recognize the potential valuation 'bias' caused by anchoring effects. As anchoring drag patent value away from their scientific quality, it may lead to considerable overvaluation or undervaluation of patents in the market. Policy makers may want to address this special type of market 'failure', to better promote high-quality innovations. If not, in a market where a strong anchoring effect distorts the association between patent quality and valuation, firms may be less motivated to strive for high-quality technological development, which would not be well recognized by the market. Our moderation analyses hint some possibilities. Patent novelty, for instance, is found to weaken the anchoring effect. Policy makers may opt to prioritize innovation endeavors that exhibit greater novelty, thereby encouraging firms to cultivate distinctive patents. This may help diminish the plausibility of prior anchors as informational cues.

4.4. Limitations and future research

Our study is not without caveats. One should be particularly cautious about the generalizability of our findings. As mentioned above, this study hinges on the creative measure of patent value by Kogan et al. (2017). While it provides useful information about short-term market valuation of patents, it is not necessarily a perfect reflection of universal patent value. First, as the market is never efficient (Cohen et al., 2013; Zuckerman and Rao, 2004), its valuation of patents can also be biased, subject to social construction. Second, because patent value is mostly realized by combining with complementary assets (e.g., manufacturing and complementary technologies) (Teece, 1986), the same patent may carry very different amounts of value in different production contexts. Third, market valuation is constantly changing, such that patent value in the long run can differ considerably from what we observe in Kogan et al. (2017). Despite those limitations, the approach by Kogan et al. (2017) is still one of the best available ways for us to both tease out patents' individual value and test the effect of anchoring on preceding patents.

Moreover, our research assumes that market audiences are aware of and attentive to preceding patent valuation. This assumption is not unreasonable, at least in our research context of stock markets where investors mostly pay close attention to information on patent grants, albeit in varying degrees (Chemmanur et al., 2022). However, we cannot offer detailed insights on how investors exactly perceive and utilize preceding patent value in their own valuation process. To better unpack the process, more (qualitative) investigation is needed. This is especially necessary, given that some of our findings suggest a "reverse anchoring" effect. Under some specific conditions, we find a negative effect of anchoring effect, such that patent valuation significantly deviates from prior anchors. That is, anchoring effect in patent valuation is not universal or unconditional. While we have provided some ad-hoc explanations, in-depth investigation is required to elucidate these unexpected findings.

In addition, it is useful to further rule out alternative explanations. Because our research design cannot identify random sources of variation in anchors, our modeling strategy ultimately does not yield ideal causal estimates. Specifically, it is possible that prior patent valuations may deliver some useful information for the estimation of focal patent value in the same class, indicating a rational learning instead of irrational anchoring. Trying to alleviate such concerns, we have followed prior studies to control for the potential vicarious learning (Malhotra et al., 2015), and conducted robustness checks with an additional control for market trend in the focal domain (see Appendix A). Still, we acknowledge the correlational nature of our findings, and expect future studies to draw clear causal inferences.

Furthermore, while our study focuses on the valuation from stock market investors, we do not know whether and how other types of audiences (e.g., customers, partners, and competitors) are subject to the anchoring effect in valuing patents. Although anchoring is not unconditional, we conjecture that it is also pervasive in many other valuation contexts. For instance, when negotiating patents' licensing fees, both parties may anchor their estimates on preceding prices (Malhotra et al., 2015); when deciding whether to renew patents, firms may consider the renewal thresholds of similar preceding patents. Nonetheless, more dedicated research is needed to test anchoring effects in these contexts.

Finally, while we focus only on the anchoring effect, future work may explore other types of behavioral heuristics (Tversky and Kahneman, 1974) that shape the valuation of patents. Prior work has long suggested

[12] Specifically, economic value usually depends on the size of market demand, whereas scientific value may not. Two patents with equally high scientific quality can have different economic value if their target markets differ in sizes. We have tried to address this in two ways. First, we include both Class × Year and Firm fixed-effects in our estimation. As a patent's potential market size is often related to its technological domain and assigning firm, these fixed-effects can help account for heterogeneity in market size. Second, in our extensional analyses in Table 6, we match each pair of patents with highest similarity, and add the Patent-Pair fixed-effects. As matched patents usually target similar markets, this may further help alleviate the concern that the decoupling of patents' scientific and economic value is simply driven by market size.

that inventive progresses depend not only on technological superiority, but also on various behavioral factors (Podolny and Stuart, 1995; Vergne, 2013). The behavioral perspective is crucial to understand the economic valuation of patents, as it largely hinges on how market stakeholders (e.g., investors, customers, and competitors) perceive them. As such, we see a promising avenue for future research to incorporate additional behavioral aspects into uncovering the patent valuation process.

CRediT authorship contribution statement

P.E.N.G.F.E.I. Wang: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Acknowledgement

I would like to thank the Editor Can Huang and two anonymous reviewers for their constructive comments in the review process, which have been very useful for me to improve the research from its initial version. All remaining errors are mine.

Appendix A. Market Trends

Table A1
Robustness Checks After Controlling for Market Trends

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Achoring effect	0.006**	0.006**	−0.021***	0.025**	−0.003
	(0.002)	(0.002)	(0.004)	(0.008)	(0.010)
Patent novelty		−0.004			−0.002
		(0.014)			(0.012)
Achoring effect × Patent novelty		−0.014*			−0.015**
		(0.006)			(0.005)
Anchors' divergence			−0.006		−0.006
			(0.009)		(0.009)
Achoring effect × Anchors' divergence			−0.072***		−0.073***
			(0.006)		(0.006)
Firm's patenting frequency				−0.097***	−0.099***
				(0.027)	(0.026)
Achoring effect × Firm's patenting frequency				0.039***	0.045***
				(0.010)	(0.010)
Vicarious learning	0.250***	0.250***	0.336***	0.244***	0.329***
	(0.022)	(0.022)	(0.024)	(0.021)	(0.022)
Predicted value of focal patent	0.977**	0.988**	0.971**	0.903**	0.893**
	(0.310)	(0.362)	(0.316)	(0.282)	(0.330)
Market trend	**0.084*****	**0.084*** **	**0.095*** **	**0.083*** **	**0.094*** **
	(0.009)	**(0.009)**	**(0.010)**	**(0.009)**	**(0.010)**
Constant	−0.127	−0.150	−0.132	0.016	0.022
	(0.640)	(0.745)	(0.651)	(0.582)	(0.682)
Firm FE	Yes	Yes	Yes	Yes	Yes
CPC class × Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	995,945	995,945	959,531	995,945	959,531
R-squared	0.870	0.870	0.874	0.872	0.877

Robust standard errors in parentheses.
***p < 0.001.
**p < 0.01.
*p < 0.05.
+p < 0.10.

Note. Market trend is measured as the average valuations of all other patents issued on the same date in the same class as the focal patent.

Appendix BIllustration of Anchoring Effect

On May 8th, 2001, there are four patents issued in our sample in the CPC class of G08 (i.e., "Signaling" technologies). In the column of *Actual value*, we report the log of the nominal value of patents according to KPSS; in the *Predicted value*, we present the predicted value of them based on our hedonic regressions according to conventional observable factors. They are mostly quite consistent, suggesting that patents' economic value is related to their observable characteristics included in our Table 2 (e.g., backward citation and novelty). Still, there is considerable divergence between the two, as reported in the column of *Actual-Predicted value*.

Anchor effect is calculated as the difference between prior patents' value and the predicted value of the focal patent. For P1 and P4, they have a negative value of anchor effect, as their predicted value is larger than prior patents' value. According to our argument, this will likely pull their actual valuation downwards. Consistent with this, we see that P1 and P4 have a lower actual value than predicted value. For P3, it has a positive value of anchor effect. Consistent with our argument, P3 has a larger actual value than predicted value, as the anchors pull its actual valuation upwards. Nonetheless, the anchoring effect is not observed in every case. Indeed, the valuation of P2 stands out as an anomaly, diverging from what we anticipate. In sum, from this simple illustration, we see a general pattern that is consistent with our core claims on anchoring, albeit with some exceptions.

As such, this hedonic approach enables us to distinctly identify several primary factors influencing patent valuation (e.g., anchoring and vicarious learning), which is our primary research focus. If without hedonic regressions, for instance, we are unable assess whether prior patents pull the valuation of a focal patent upwards or downwards from its observable characteristics, and cannot capture the extent to which prior patents have been over- or under-valuated (i.e., market trend).

Table A2
Examples for anchoring in our sample.

Issue Date	ID	Patent No.	Actual value (Vp)	Predicted value (πp)	Actual-Predicted value (Vp-πp)	Anchor effect (Vp-1-πp)	Vicarious learning (Vp-1-πp-1)	Prior value (Vp-1)
May/8/2001	P1	6229435	2.50	2.69	−0.19	−1.55	−0.20	1.14
May/8/2001	P2	6229442	3.47	3.04	0.43	−1.89	−0.20	1.14
May/8/2001	P3	6226997	0.66	0.58	0.08	0.56	−0.20	1.14
May/8/2001	P4	6230011	1.52	2.59	−1.08	−1.45	−0.20	1.14

From the example, we can also understand why we do not use the absolute value of anchor effect. For P1, its negative anchor effect is likely to depress its valuation below the predicted level. Conversely, if we were to use its absolute value, the anchoring effect would imply an even higher valuation of P1 than predicted. However, this is evidently not the case.

References

Abrams, D.S., Akcigit, U., Grennan, J., 2013. Patent Value and Citations: Creative Destruction or Strategic Disruption? National Bureau of Economic Research.
Alcácer, J., Gittelman, M., Sampat, B., 2009. Applicant and examiner citations in US patents: an overview and analysis. Res. Pol. 38 (2), 415–427.
Arora, A., Cohen, W., Lee, H., Sebastian, D., 2023. Invention value, inventive capability and the large firm advantage. Res. Pol. 52 (1), 104650.
Arts, S., Cassiman, B., Gomez, J.C., 2018. Text matching to measure patent similarity. Strat. Manag. J. 39 (1), 62–84.
Beggs, A., Graddy, K., 2009. Anchoring effects: evidence from art auctions. Am. Econ. Rev. 99 (3), 1027–1039.
Bessen, J., 2008. The value of US patents by owner and patent characteristics. Res. Pol. 37 (5), 932–945.
Bessen, J., 2009. Estimates of patent rents from firm market value. Res. Pol. 38 (10), 1604–1616.
Bikhchandani, S., Hirshleifer, D., Welch, I., 1998. Learning from the behavior of others: Conformity, fads, and informational cascades. J. Econ. Perspect. 12 (3), 151–170.
Brambor, T., Clark, W.R., Golder, M., 2006. Understanding interaction models: Improving empirical analyses. Political analysis 14 (1), 63–82.
Bronzini, R., Piselli, P., 2016. The impact of R&D subsidies on firm innovation. Res. Pol. 45 (2), 442–457.
Chemmanur, T.J., Li, D., Tseng, K., Wang, Y.Y., 2022. Measuring the Economic Value of an Innovation when Some Investors Are Inattentive: Theory and Evidence. Available at: SSRN 3504261.
Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. Rev. Financ. Stud. 26 (3), 635–666.
Connelly, B.L., Certo, S.T., Ireland, R.D., Reutzel, C.R., 2011. Signaling theory: a review and assessment. Journal of management 37 (1), 39–67.
Correia, S., 2016. reghdfe: estimating linear models with multi-way fixed effects. Paper Presented at the 2016 Stata Conference.
Dahlstrand, Å.L., 1997. Growth and inventiveness in technology-based spin-off firms. Res. Pol. 26 (3), 331–344.
Dass, N., Nanda, V., Xiao, S.C., 2017. Truncation bias corrections in patent data: implications for recent research on innovation. J. Corp. Finance 44, 353–374.
de Wilde, T.R., Ten Velden, F.S., De Dreu, C.K., 2018. The anchoring-bias in groups. J. Exp. Soc. Psychol. 76, 116–126.
Epley, N., 2004. A tale of tuned decks? Anchoring as accessibility and anchoring as adjustment. The Blackwell handbook of judgment and decision making 240–256.
Essendorfer, S., Diaz-Rainey, I., Falta, M., 2015. Creative destruction in Wall Street's technological arms race: evidence from patent data. Technol. Forecast. Soc. Change 99, 300–316.
Fleming, L., 2001. Recombinant uncertainty in technological search. Manag. Sci. 47 (1), 117–132.
Fleming, L., Mingo, S., Chen, D., 2007. Collaborative brokerage, generative creativity, and creative success. Adm. Sci. Q. 52 (3), 443–475.
Furnham, A., Boo, H.C., 2011. A literature review of the anchoring effect. J. Soc. Econ. 40 (1), 35–42.
Gambardella, A., 2013. The economic value of patented inventions: Thoughts and some open questions. Int. J. Ind. Organ. 31 (5), 626–633.
Gambardella, A., Harhoff, D., Verspagen, B., 2008. The value of European patents. Eur. Manag. Rev. 5 (2), 69–84.
Gambardella, A., Harhoff, D., Verspagen, B., 2017. The economic value of patent portfolios. J. Econ. Manag. Strat. 26 (4), 735–756.
Genesove, D., Mayer, C., 2001. Loss aversion and seller behavior: evidence from the housing market. Q. J. Econ. 116 (4), 1233–1260.
Giuri, P., Mariani, M., Brusoni, S., Crespi, G., Francoz, D., Gambardella, A., Garcia-Fontes, W., Geuna, A., Gonzales, R., Harhoff, D., 2007. Inventors and invention processes in Europe: results from the PatVal-EU survey. Res. Pol. 36 (8), 1107–1127.
Gruber, M., Harhoff, D., Hoisl, K., 2013. Knowledge recombination across technological boundaries: Scientists vs. engineers. Manag. Sci. 59 (4), 837–851.
Hall, B.H., Harhoff, D., 2012. Recent research on the economics of patents. Annu. Rev. Econ. 4 (1), 541–565.
Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. Rand J. Econ. 16–38.
Harhoff, D., Narin, F., Scherer, F.M., Vopel, K., 1999. Citation frequency and the value of patented inventions. Rev. Econ. Stat. 81 (3), 511–515.
Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. Res. Pol. 32 (8), 1343–1363.
Harhoff, D., Wagner, S., 2009. The duration of patent examination at the European Patent Office. Manag. Sci. 55 (12), 1969–1984.
Higham, K., De Rassenfosse, G., Jaffe, A.B., 2021. Patent quality: towards a systematic framework for analysis and measurement. Res. Pol. 50 (4), 104215.
Hirshleifer, D., Hsu, P.-H., Li, D., 2018. Innovative originality, profitability, and stock returns. Rev. Financ. Stud. 31 (7), 2553–2605.
Hsu, D.H., Hsu, P.-H., Zhou, T., Ziedonis, A.A., 2021. Benchmarking US university patent value and commercialization efforts: a new approach. Res. Pol. 50 (1), 104076.
Hsu, D.H., Ziedonis, R.H., 2013. Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents. Strat. Manag. J. 34 (7), 761–781.
Huang, K.G.-L., Huang, C., Shen, H., Mao, H., 2021. Assessing the value of China's patented inventions. Technol. Forecast. Soc. Change 170, 120868.
Kaplan, S., Vakili, K., 2015. The double-edged sword of recombination in breakthrough innovation. Strat. Manag. J. 36 (10), 1435–1457.
Khanna, R., 2023. Passing the torch of knowledge: Star death, collaborative ties, and knowledge creation. Res. Pol. 52 (1), 104649.
Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Q. J. Econ. 132 (2), 665–712.
Kok, H., Faems, D., de Faria, P., 2019. Dusting off the knowledge shelves: Recombinant lag and the technological value of inventions. J. Manag. 45 (7), 2807–2836.
Lerner, J., Seru, A., 2022. The use and misuse of patent data: issues for finance and beyond. Rev. Financ. Stud. 35 (6), 2667–2704.
Lerner, J., Strojwas, M., Tirole, J., 2007. The design of patent pools: the determinants of licensing rules. Rand J. Econ. 38 (3), 610–625.
Lindner, T., Puck, J., Verbeke, A., 2020. Misconceptions about Multicollinearity in International Business Research: Identification, Consequences, and Remedies, vol. 51. Springer, pp. 283–298.
Luchman, J.N., 2021. Determining relative importance in Stata using dominance analysis: domin and domme. STATA J. 21 (2), 510–538.
Malerba, F., Orsenigo, L., 1993. Technological regimes and firm bebavior. Ind. Corp. Change 2 (1), 45–71.
Malhotra, S., Zhu, P., Reus, T.H., 2015. Anchoring on the acquisition premium decisions of others. Strat. Manag. J. 36 (12), 1866–1876.
Meub, L., Proeger, T., 2018. Are groups 'less behavioral'? The case of anchoring. Theor. Decis. 85, 117–150.
Moser, P., Ohmstedt, J., Rhode, P.W., 2018. Patent citations—an analysis of quality differences and citing practices in hybrid corn. Manag. Sci. 64 (4), 1926–1940.
Mowery, D.C., Ziedonis, A.A., 2002. Academic patent quality and quantity before and after the Bayh–Dole act in the United States. Res. Pol. 31 (3), 399–418.
Mussweiler, T., 2003. Comparison processes in social judgment: mechanisms and consequences. Psychol. Rev. 110 (3), 472.

Northcraft, G.B., Neale, M.A., 1987. Experts, amateurs, and real estate: an anchoring-and-adjustment perspective on property pricing decisions. Organ. Behav. Hum. Decis. Process. 39 (1), 84–97.
Odasso, C., Scellato, G., Ughetto, E., 2015. Selling patents at auction: an empirical analysis of patent value. Ind. Corp. Change 24 (2), 417–438.
Podolny, J.M., Stuart, T.E., 1995. A role-based ecology of technological change. Am. J. Sociol. 100 (5), 1224–1260.
Rao, H., Greve, H.R., Davis, G.F., 2001. Fool's gold: social proof in the initiation and abandonment of coverage by Wall Street analysts. Adm. Sci. Q. 46 (3), 502–526.
Righi, C., Simcoe, T., 2019. Patent examiner specialization. Res. Pol. 48 (1), 137–148.
Rindova, V.P., Petkova, A.P., 2007. When is a new thing a good thing? Technological change, product form design, and perceptions of value for product innovations. Organ. Sci. 18 (2), 217–232.
Sailors, J.J., Heyman, J.E., 2019. Similarity, multiple estimations, and the anchoring effect. J. Gen. Psychol. 146 (2), 200–215.
Schumpeter, J.A., 1983. The Theory of Economic Development: an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. Transaction Publishers.
Sime, S., Hagedoorn, J., Hui, T., 2023. Innovation performance and licensing: the effect of the compositional quality of direct and indirect network ties. Technovation 127, 102826.
Singh, A., Triulzi, G., Magee, C.L., 2021. Technological improvement rate predictions for all technologies: use of patent data and an extended domain description. Res. Pol. 50 (9), 104294.
Strack, F., Mussweiler, T., 1997. Explaining the enigmatic anchoring effect: mechanisms of selective accessibility. Journal of personality and social psychology 73 (3), 437.
Teece, D.J., 1986. Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. Res. Pol. 15 (6), 285–305.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. Rand J. Econ. 172–187.
Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. science 185 (4157), 1124–1131.
Vergne, J.-P., 2013. QWERTY is dead, long live path dependence. Res. Pol.
Zuckerman, E.W., Rao, H., 2004. Shrewd, crude or simply deluded? Comovement and the internet stock phenomenon. Ind. Corp. Change 13 (1), 171–212.