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Patents and Supra-competitive Prices: Evidence from Consumer Products

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Abstract

A patent system is a central tool in innovation policy. The prospect of monopolistic pricing supposedly encourages firms to innovate. However, there is scant empirical evidence supporting the existence of higher markups for patent-protected products. Using an original dataset that links consumer products to the patents that protect them, we study the impact of patent protection on product prices. Exploiting exogenous variations in patent status, we find that a loss of patent protection leads to an 8–10 percent drop in product prices. The price drop is larger for more important patents and is more pronounced in more competitive product markets.

Keywords: innovation, markup, patent system, product, R&D incentive

JEL Codes: O31, O34, L11, D42, K11

1 Introduction

Innovation, which is a key driver of productivity growth ([Romer, 1990](#); [Aghion and Howitt, 1992](#)), is subject to several well-documented market failures that lead to under-investment in R&D activities (e.g., [Martin and Scott, 2000](#); [Bloom et al., 2019](#)). Consequently, governments incentivize R&D investments using a variety of policy instruments. One such instrument is the patent system, which offers inventors a temporary exclusion right over their inventions. This right allegedly allows inventors to charge monopolistic prices for their products, enabling them to recoup their R&D investments ([Plant, 1934](#); [Arrow, 1962](#); [Nordhaus, 1969](#)).

The theoretical literature assumes that a monopoly over an invention translates into an ability to charge supra-competitive prices in the product market. However, it is not clear that this is always the case. For instance, competitors could invent around the original patented invention and offer a product with similar features to the end consumer, thereby breaking down market exclusivity. Moreover, recurring discussions about the dubious validity of issued patents (e.g., [Lemley and Shapiro, 2005](#); [Jaffe and Lerner, 2011](#)), adds another reason to be skeptical. If patents do not allow innovators to sustain supra-competitive prices, the main argument about the effectiveness of the patent system in encouraging innovation falls apart.

To the best of our knowledge, empirical research on the effect of patents on product prices has been limited to drugs. Yet, many observers would agree that drugs offer a very favorable setup for testing the effectiveness of patent protection. First, a patent protects the molecule of a drug and grants full exclusivity on its use—the patent and the product are, therefore, virtually the same. Second, the costs of drug innovation are very high, whereas imitation costs are comparatively low, making the industry prone to free-rider problems and patent protection all the more relevant. These arguments help explain the recurring finding that patent protection is particularly effective for the pharmaceutical industry compared to other industries ([Mansfield, 1986](#); [Levin et al., 1987](#); [Harabi, 1995](#);

Cohen et al., 2000). However, the patent system has not been designed for drugs alone. Despite the centrality of the ‘monopoly pricing hypothesis’ for justifying the existence of intellectual property (IP) rights, evidence on other industries is scant. The main challenge preventing progress in the field lies in linking patents to products.

This paper empirically examines the effect of patent protection on the price of an array of consumer products. We collect original data on patent-product associations and study the effect of an exogenous *loss* of patent protection on product prices. We have matched 2778 patents to 825 products available on the Amazon.com e-commerce website and have tracked the prices of these products for a period of up to eight years. We study the change in price around the time of patent expiry. Because patent protection is limited in time by law, patent expiry is exogenous to the quality of the underlying invention or to its commercial value. Furthermore, we have sought to carefully isolate the effect of patent expiry from the effect of product obsolescence by controlling for product model displacement and product age. The empirical analysis then explores the heterogeneous effects of patent expiry across patent types and importance. It also portrays the price evolution around the time of patent expiry. Finally, it considers how prices react to the intensity of the competition in the product market.

We find that patent expiry is associated with an 8–10 percent drop in product prices and that the effect is larger for more important patents (i.e., patents protecting more products). Products with expired patents are also more likely to be out of stock, which is consistent with lower markups (Bils, 2016). We observe that the price starts dropping about one year *before* patent expiry, possibly suggesting the use of price reduction as a strategic entry deterrence from the incumbent, as observed in the airline and pharmaceutical industries (Milgrom and Roberts, 1982; Goolsbee and Syverson, 2008; Tenn and Wendling, 2014). We also observe that the decline in price is more pronounced in more competitive markets, with some evidence of a U-shape relationship between the price drop and the level of competitive pressure. Furthermore, the price drop is stronger in environments where patent protection is known to be an effective appropriation mechanism. Finally, placebo tests on samples of fake patent expiry events strengthen our confidence

in the validity of the empirical modeling strategy.

The paper adds to the rich and long-standing debate on the effectiveness of IP rights in stimulating innovation (summarized in [Hall, 2007](#); [Lerner, 2009](#); [Budish et al., 2016](#)). Overall, the results provide evidence that patent protection supports higher price premiums—innovators seem to be able to charge supra-competitive prices during patent protection. Furthermore, the estimates we obtain are important to quantify the extent of the subsidy conferred by the patent system (e.g., [Schankerman, 1998](#)). Similarly, the 8–10 percent figure helps us understand the cost of the patent system that consumers bear in exchange of more innovative products. The paper also adds to the literature on the economic valuation of patents. Scholars have proposed a variety of approaches to estimate patent value (e.g., [Hall et al., 2007](#); [Bessen, 2008](#); [Arora et al., 2008](#); [Kogan et al., 2017](#)) but none have exploited the source of data we use.

The paper is organized as follows. Section 2 provides background information on what we call the monopoly pricing hypothesis. Section 3 presents our empirical research design. Section 4 explains the construction of the dataset and introduces the main variables. Section 5 reports our findings and Section 6 offers concluding remarks.

2 Background

2.1 The monopoly pricing hypothesis of patents

Following [Arrow \(1962\)](#) and [Nordhaus \(1969\)](#), a vast theoretical literature has studied the design of patent systems. Contributions have looked into the optimal duration, strength, breadth, and scope of patent protection under various industry structures and invention types (e.g., [Kamien and Schwartz, 1974](#); [Judd, 1985](#); [Waterson, 1990](#); [Gilbert and Shapiro, 1990](#); [Klemperer, 1990](#); [Denicolo, 1996](#); [Matutes et al., 1996](#); [O’Donoghue et al., 1998](#); [Erkal, 2005](#); [Acemoglu and Akcigit, 2012](#)).

Models of the patent system take different forms, but the core principle works as

follows. It is notoriously difficult for innovators to exclude third parties from using knowledge, which undermines innovators' ability to recoup the investments in generating the knowledge, thus creating a gap between the private returns to inventive activities and the social returns. As a result, competitive markets under-incentivize private research investments compared to the social planner's preference. Governments intervene by granting a monopoly right over inventions in order to increase appropriability. The welfare loss created by this monopoly right is offset by the dynamic efficiency of increased investments in inventive activities.

The theoretical literature implicitly equates *monopoly over an invention* with *monopoly over a product*. That is, it assumes that patent protection (covering an invention) allows the firm to charge supra-competitive prices (for the product). This assumption is far from obvious. First, an invention does not come in the form of a finished product ready for sale. The inventor must undertake costly and risky development and testing to transform the invention into a commercially viable product (Sichelman, 2009).¹ Second, the U.S. Patent and Trademark Office (USPTO) has been criticized for issuing low-quality patents, in the sense that many patents would not stand up in court if litigated (Lemley and Shapiro, 2005; Bessen et al., 2008; Jaffe and Lerner, 2011). If patents are indeed "worthless" (Moore, 2005), the actual protection they offer might be substantially weaker than we assumed. Third, a monopoly over an invention, even if a patent is legally solid, does not necessarily translate into a monopoly over the final product. The next section explains this latter point in greater detail taking the computer mouse as an example.

2.2 Patent protection and product price

Patent protection typically offers a monopoly over a specific feature of a final product, which may translate into an increase in product quality or a broadening of product variety

¹Note that invention owners may recoup their R&D investments not by commercialization in the product market but by licensing or selling their inventions to competitors (Arora et al., 2004). In markets for technologies, the actual invention *is* the good being traded. Several studies have documented the prime role of patent protection in markets for technologies (Gans et al., 2008; de Rassenfosse et al., 2016). The present paper focuses on product commercialization.

(e.g., Horstmann et al., 1985; Waterson, 1990). These features may or may not allow the firm to charge supra-competitive prices.

To illustrate, let us consider the case of the computer mouse. Some inventions in this area are truly radical and pave the way for an entirely new product market. U.S. patent 3,541,541, entitled “X-Y Position Indicator for a Display System,” falls in this category. The patent, filed by Douglas Engelbart in 1967, is known as the first computer mouse patent. The technology was licensed to Apple, Xerox, and a few other companies, creating *de facto* a market oligopoly.² Computer mice at the time sold between \$200–\$400, equivalent to \$600–\$1200 in 2024 prices.³ Since then, technological progress regarding the computer mouse has taken many forms.

Consider, first, the case of inventions that increase product quality. A radical technological shift occurred with the first optical mouse, which offered a superior solution compared to traditional mechanical mice—preventing dirt from getting stuck inside the mouse. The shift from mechanical to optical mouse was one of the main advances in this market, but optical mice still perform the same function as mechanical mice. This technology shift represents an improvement in product quality that can command a higher price. Another radical shift occurred with the first touchpad patent, U.S. Patent 5,305,017, which created a substitute technology—indeed, a new product, at least for the laptop market segment.

However, new technologies do not necessarily improve product quality or create entirely new product families. For example, optical mice may rely either on lasers or on LEDs but function in the same way for the end user and offer otherwise similar features. The existence of two substitute technologies to address the same problem breaks down the exclusivity over optical mice, and exemplifies that exclusivity over an invention does not guarantee market exclusivity.

Next, consider the case of inventions that broaden product variety either by segment-

²Sadly for the inventor, the invention was not commercially viable until 1984 when Apple released the Macintosh, three years before the patent’s expiration. See <https://www.doungelbart.org>, last accessed on December 1st, 2024.

³Source: <https://www.macworld.com>, last accessed on December 1st, 2024.

ing the market or by adding functionalities. Regarding market segmentation, adding more lasers on an optical mouse improves the tracking precision. This feature may appeal to a specific consumer segment such as gamers, who are willing to pay a higher price—but again, there are many ways to improve the tracking precision. Sometimes, inventions are developed to serve lower-end segments—indeed, ‘frugal innovation’ and ‘innovation by subtraction’ offer alternative ways of developing new products (e.g., [Hart and Christensen, 2002](#)). This is the case for Logitech’s U.S. patent 7,030,857, which is typically associated with lower-end mice of the M series, such as the ‘M100 Mouse.’ Regarding functionalities, an invention may add a feature, which may turn out to be adopted widely, such as the scrolling wheel (U.S. patent 5,313,230), or abandoned, such as the side click.

In a nutshell, the relationship between patent protection and product price is complex: some patents can be invented around, others may cover lower-end versions of a product, and others may turn out to be commercial flops. As far as we can ascertain, the effect of patents on product prices has not been tested empirically, with the notable exception of pharmaceuticals. The next section reviews the scholarly evidence in the pharmaceutical industry.

2.3 The case of the pharmaceutical industry

The pharmaceutical industry offers an obvious set-up for studying the effect of patent protection on product prices. The drug discovery and development process is costly and risky. R&D expenditure for each new molecular entity is estimated at \$1.8 billion; meanwhile, the average success rate from the pre-clinical stage to launch is estimated at about 8 percent ([Paul et al., 2010](#)). Furthermore, drugs are so-called ‘discrete’ products with a well-identified ‘invention’ (i.e., an active ingredient) clearly described in the patent specification. By granting market exclusivity over the molecular entity, patents are an efficient way to deter imitators from entering the product market for a branded drug. In contrast to the high R&D costs for developing a new drug, the production of drug is relatively cheap, and patent-protected drugs are usually sold with a high markup ([Scott Morton](#)

and Kyle, 2011). This setup is particularly attractive for generic manufacturers, who enter the market as soon as drugs lose patent protection (Scott Morton, 1999, 2000).

A host of studies has investigated the effect of patent protection on the price of drugs. This stream of research has been facilitated by data on the correspondence between drugs and patents compiled in the Orange Book Datafiles by the U.S. Food and Drugs Administration (FDA). Studies typically focus on the evolution of drug price around the time of patent expiry. Since patents are valid for a limited period of time, patent expiry is an exogenous event, allowing scholars to establish the causal impact of (a loss of) patent protection on price.

Using data on 30 drugs that lost patent protection in the 1976–87 period, Caves et al. (1991) estimate that the innovator’s price declines by 4.5 percent on average. Furthermore, generic substitutes are sold about 17 percent below the innovator’s pre-entry price. They attribute the relatively small price decline of the branded drug to the “loyalty-inducing goodwill” accumulated by the innovator during the period of patent protection. Grabowski and Vernon (1992) examine prices and market shares of 18 drugs turning off-patent after the implementation of the 1984 Drug Price Competition and Patent Term Restoration Act, which eased the testing requirements for entry by generic drugs in the United States. They find that prices for most branded drugs did not react strongly to entry; nominal prices continued to increase following roughly the same trend as during the pre-entry period. They attribute this result to the strength of brand loyalty for branded drugs. By contrast, generic drugs quote prices that are 39 percent lower than branded drugs at date of entry, and prices of generic drugs decrease sharply over time.

The low sensitivity of the price of off-patent branded drugs has been confirmed by most studies (cf. Wiggins and Maness, 2004), both in the United States (Frank and Salkever, 1997) and Europe (Vandoros and Kanavos, 2013). However, the features of the drugs market make generalization to other product markets perilous. When drugs are for repeated use, consumers may have developed a strong preference for the branded version during patent protection. Besides, concerns about perceived quality for the generic

versions and recommendations from doctors may exacerbate brand loyalty.

3 Empirical approach

The goal of the econometric analysis is to quantify the effect of a loss of patent protection on product prices.

3.1 Identification strategy

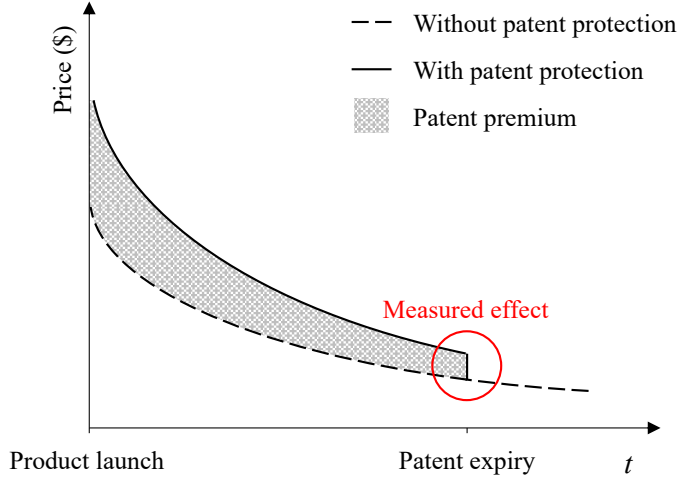
The present study exploits observational data on the price of patent-protected products that lose patent protection. There are three ways in which a product can lose patent protection. First, patents can be challenged in court and be invalidated. [Galasso and Schankerman \(2015\)](#) exploit data on invalidations to study the effect of patents on cumulative innovation. However, invalidations are rare events. [Lemley and Shapiro \(2005\)](#) estimate that a mere 0.1 percent of patents are litigated to trial. Second, the patent owner may decline to pay the renewal fees required to keep the patent in force. The patent consequently lapses and falls in the public domain—everyone is then free to use the invention. This source of variation is not appropriate for our purpose because the decision to let a patent lapse is presumably endogenous to the underlying product’s commercial success and, therefore, to its price. Third, the patent is held active until the maximum allowed term (usually 20 years) and automatically expires after that period. This event is exogenous to product quality, and there is nothing that the firm can do to prevent expiry. Our identification strategy exploits variations in product price around the time of patent expiry, as illustrated in Figure 1.⁴

Although the patent expiry event is exogenous to the firm, its exact date is known and the firm can adapt accordingly. For instance, it could launch a new generation of the

⁴[Arora et al. \(2008\)](#) and [Jensen et al. \(2011\)](#) use the term ‘patent premium’ to indicate the proportional increase in value to an invention due to patent protection. In the context of the present analysis, the patent premium would correspond to the gray area in Figure 1. Multiplied by the quantities sold at each period, the patent premium corresponds to the overall surplus that the firm can extract throughout the life of the patent.

product in an attempt to capture the most profitable market segment (Chandy and Tellis, 1998; Van Heerde et al., 2010). Consequently, the econometric regression will control for a series of potential confounding factors. Note that filing new patent applications to protect some features of the original product is not possible. Any unpatented invention embedded in the product would have long been part of prior art—and, therefore, no longer patentable—under U.S. patent law.

Figure 1: Schematic representation of the measured effect



Notes: The shapes of the price slopes and the gray area are arbitrary.

3.2 Econometric model

We exploit variations in patent status in a three-dimensional panel setting. The unit of analysis is the natural log price P in month t for product i protected by patent j .⁵ The main panel specification is as follows:

$$\log P_{ijt} = \beta_0 + \beta_1 \text{Expired}_{jt} + \beta_2 \text{ProdAge}_{it} + \beta_3 \text{NewGeneration}_{it} + \mathbf{X}_{ijt}\boldsymbol{\gamma} + \mu_{ij} + \epsilon_{ijt} \quad (1)$$

The variable of interest, Expired_{jt} , is a dummy variable that takes value 1 if patent j is expired in month t , and 0 if the patent is still active. All variables are formally introduced in the next section. The parameter of interest, β_1 , captures the change in product price

⁵It is common to model product prices in the log linear form (e.g., Brynjolfsson and Kemerer, 1996; Milyo and Waldfogel, 1999; Ashenfelter, 2008).

associated with patent expiry.

One empirical challenge lies in the fact that the price of a given product will tend to decline over time naturally. Therefore, the coefficient β_1 may simply capture the effect of the passing of time.⁶ Our solution to this issue is twofold. First, we control for the effect of the passing of time using product age (variable $ProdAge_{it}$) as well as various non-linear specifications ($ProdAge_{it}^2$ and $\log ProdAge_{it}$).⁷ Second, we also perform a placebo test where we randomly assign a fake treatment date and compare placebo estimates with baseline estimates. The placebo estimates are subject to the natural price decline but not to the expiry events. Therefore, comparing estimates obtained with placebo dates and actual dates informs us about the validity of the empirical setup.

Although patent expiry is exogenous to the firm and the product, the date of patent expiry is known. A firm can, therefore, release a new model of the product in anticipation of patent expiry. The regression model controls for the variable $NewGeneration_{it}$ to absorb the effect of product displacement. It takes value 1 if a newer version of product i is available in month t (and all the months afterwards), and 0 otherwise.

The $1 \times K$ vector $\mathbf{X}_{ijt}$ includes a set of K control variables. Its exact composition varies depending on model specification. It includes the intensity of competition as well as patent-level variables. It also includes a set of dummy variables for each calendar month in order to absorb the effect of seasonal sales and promotional offers. Finally, it includes a set of dummy variables that capture the source of the price information (variables $S_{1-4}^{A/L}$, defined below).

As the next section explains, our data are many-to-many matches between products and patents. Consequently, we are able to control for product-patent pair fixed effect (μ_{ij}) to capture time-invariant idiosyncratic characteristics such as the technological content of a patent, its importance for the product or other unobserved product characteristics. In alternative specifications, we will also include individual product and patent fixed effects

⁶A first-difference specification (ΔP_{ijt}) would not address this issue satisfactorily because the general price decline might not be constant over time, and the possible drop in price might not be contemporaneous to patent expiry.

⁷Specifications with yearly or monthly age dummies produce similar results.

(μ_i and μ_j , respectively).

Finally, ϵ_{ijt} is the error term. Given the multi-level structure of our data, standard errors can be clustered at various levels. Clustering at the patent level allows for correlation across products and months associated with the same patent, while clustering at the product level accounts for persistent market- or cost-level shocks. Since our treatment varies at the patent level, we report standard errors clustered at that level. However, our main results are robust to both product-level and two-way clustering (Cameron et al., 2011).⁸

4 Data and variable construction

Studying the effect of patents on product prices calls for three elements: data on the products, data on the patents, and a way to link products to patents. Establishing the link between products and patents is the most challenging part, and we start by presenting our novel approach to doing so. We then turn to data on products and on patents. The final dataset is a monthly unbalanced panel of 489,878 observations associated with 14,621 product-patent pairs corresponding to 825 patented products (covered by 2778 patents) for the period 2011–2019.

4.1 Data on product-patent links

We collected data on the link between products and patents by manually searching for Virtual Patent Marking (VPM) web pages of consumer good companies. VPM was introduced in U.S. patent law under the 2011 Leahy-Smith America Invents Act (AIA). The AIA allows patentees to affix the word “patent” or “pat.” on the product along with a URL of a web page that associates the patented product with the patent number(s). The marking statute enables patentees to give public notice that the article is patented, which

⁸Two-way clustering is computationally demanding and, in some cases, absorbs so much variation that insufficient variation remains in the key regressor to reliably estimate its standard error. This motivates our choice to report patent-level clustering as the baseline.

can prove useful in infringement cases. [de Rassenfosse \(2018\)](#) explains that patentees have incentives to disclose information accurately because listing patents that do not cover a product exposes them to false marking suits.

Before delving further into the data, a note of caution is warranted. The marking statute provides firms with an incentive to list patents that they *own*. Manufacturing firms do not care as much if the patents they license from other firms are being infringed—indeed, it is usually the patent owner that files infringement suits, not the licensee. Thus, we may not have complete information on the patent coverage for products that involve licensed patents.⁹ Having noted this data limitation, a lack of data on licensed patents does not threaten our empirical analysis. Indeed, there is no reason to suspect that the timing of patent filing (and, therefore, expiry) for licensed patents exactly and systematically coincides with that of the innovator’s own patents. Thus, from an econometric viewpoint, the expiry of licensed patents should merely generate noise in the price series.

We obtained product-patent information for 825 products sold in the United States by 77 firms. Products are all consumer goods available on the Amazon.com e-commerce website. We classify products using the 13 Amazon ‘Departments’ to which they belong (henceforth, product categories). For example, the ‘Appliances’ category includes the ‘Dyson DC35 Cordless Stick Vacuum’ and the ‘Emerson CF830 Ceiling Fan.’ Table 1 provides an overview of the number of firms, products, patents, and transacted patents (licensed or transferred) by product category.¹⁰ ‘Electronics’ is the most populated category, covering close to 40 percent of products and 50 percent of patents. Appendix Table A.1 presents a list of representative products sold by each firm.

⁹However, licensors may require licensees to mark their products with the licensed patents, such that we have some licensed patents in the sample. We will exploit this information in a robustness test.

¹⁰Since we observe both who is the original patent assignee listed in the patent document and who claims the patent on the VPM webpage, we are able to infer which patents have been transacted on the market for technology. Section 5.2.2 provides additional details.

Table 1: Summary of firms, products, and patents by product category

Product category	No. firms	No. products	No. patents	No. transacted patents
Appliances	4	52	335	0
Automotive Parts	5	117	118	10
Baby Products	2	7	15	0
Clothing, Shoes & Jewelry	2	7	14	0
Electronics	23	310	1348	25
Health & Household	6	163	357	23
Industrial & Scientific	7	17	33	0
Musical Instruments	2	13	71	0
Office Products	5	21	81	2
Software	2	9	189	0
Sports & Outdoors	8	40	54	5
Tools & Home Improvement	10	36	135	1
Video Games	1	33	28	16
Total	77	825	2778	82

Table 2 shows the number of patents per product, which can be seen as a measure of the ‘complexity’ of products.¹¹ The median number of patents per product is 4, but the variable is highly skewed. In some categories, such as ‘Electronics’ and ‘Software,’ a quarter of products are covered by more than 77 and 66 patents, respectively. The table also presents the complementary figure, namely, the number of products protected by the same patent. It is a measure of patent importance. A patent protects a median number of two products in our sample.

¹¹The literature offers several definitions of complex products. They are characterized by a “complex web of dependencies and interactions between the modules” (Sharman and Yassine, 2004), they are “high cost, engineering-intensive products” (Hobday, 1998), and their development involves a “large number of both physical components and design participants” (Sosa et al., 2004). In this paper, we define complex products as products involving multiple patented components.

Table 2: Patent and product intensity

Product category	Patents per product			Products per patent		
	Bottom 25%	Median	Top 25%	Bottom 25%	Median	Top 25%
Appliances	1.5	16	35	1	2	4
Automotive Parts	1	1	2	1	1	2
Baby Products	1	2	2	1	1	1
Clothing, Shoes & Jewelry	4	5	6	1	3	3
Electronics	2	8	77	1	3	7
Health & Household	2	5	9	1	2	3
Industrial & Scientific	2	3	4	1	1	2
Musical Instruments	1	2	5	1	1	1
Office Product	1	4	6	1	1	1
Software	13	38	66	2	2	2
Sports & Outdoors	1	3	5	1	2	4
Tools & Home Improvement	1.5	2.5	5.5	1	1	2
Video Games	3	3	4	1	1	1
Total	1	4	11	1	2	5

4.2 Data on products

All products in our sample are (or were) available for purchase on the U.S. platform of Amazon.com. We manually searched for the products on Amazon.com, with a view of recovering the ASINs, the unique product identifiers.¹² We then collected various information about the products in our sample.

Product price

We obtained the price history for all products using *Keepa*, a commercial price-comparison web service that provides historic price data since 2011.¹³ *Keepa* tracks Amazon’s products several times per day and records their prices and inventory status (in-stock and out-of-stock).

In general terms, online retail prices are affected by the structure of the distribution platforms connecting sellers and buyers. Distributors, retailers, and platforms all take a

¹²The Amazon Standard Identification Number (ASIN) is a 10-character alphanumeric unique identifier used for product identification within the Amazon organization. It is a very granular identifier, corresponding to the individual products that can be bought on the platform.

¹³See <http://www.keepa.com>, last accessed on December 1st. This service has already been used in academic research, see, e.g., [Reimers and Waldfogel \(2020\)](#).

share of the final price. A vast literature has emerged that studies online prices under various angles (e.g., [Clay et al., 2001](#); [Tang et al., 2010](#); [Cavallo, 2017](#)). Amazon is an e-commerce platform that offers buyers a variety of products, both homogeneous and differentiated. In the context of our study, the products in our sample can be regarded as differentiated since they all contain various patented features. The platform is also fairly transparent about price differences between sellers for the same product and the availability of alternative, similar products.

We use two prices: the Amazon price (P^A) and the List price (P^L). The Amazon price is the actual sales price at which an article is sold, i.e., the retail price. The List price is suggested by the manufacturer and does not always correspond to the Amazon price.¹⁴ The Amazon price corresponds to the market price and, therefore, forms our baseline measure of price. However, the Amazon price typically exhibits greater variability than the list price, with temporary discounts (e.g., upon the release of a new product) or price hikes. Accordingly, we also report estimates performed using the List price for the sake of robustness.

In order to have a balanced panel, we impute empty price data for both the Amazon price and the list price indices.¹⁵ For both indices, we first reconstruct the daily price series, which we then average by month. We follow some simple rules to impute empty price data for the daily series. Regarding the Amazon price index, if there is a gap in the Amazon price series while the product is in stock, we populate the empty data with the last known Amazon price. If there is a gap in the Amazon price series while the product is out of stock, we populate the empty data with the last known List price. If the List price is not available (out-of-stock), we again populate the empty data with the last known in-stock Amazon price. We perform the mirror operation for the list price index. Next, we average the daily prices by month and take the natural logarithm to obtain the dependent variables P^A and P^L .

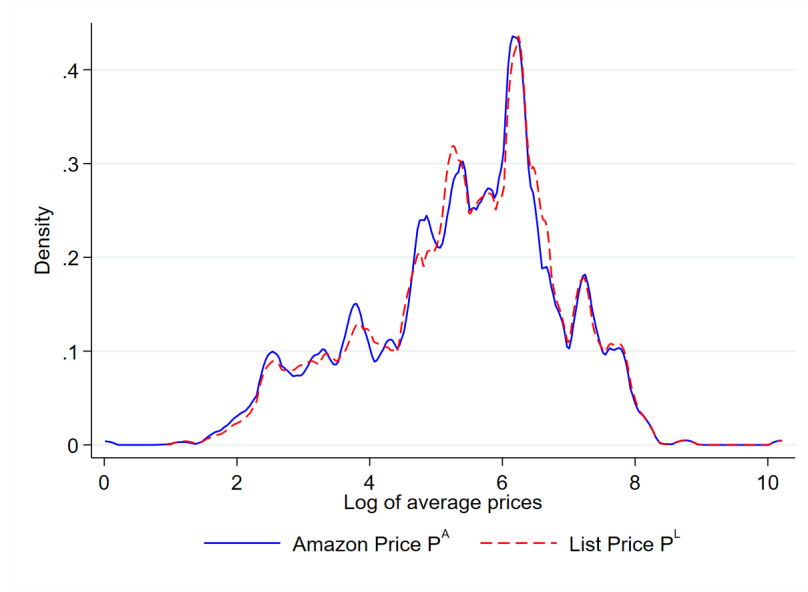
¹⁴On average, the Amazon price is 9.6 percent lower than the List price.

¹⁵*Keepa* records the prices for an item whenever a change occurs. Therefore, empty data on prices means either that the price has remained stable (such that no price was recorded) or that the item was temporarily out-of-stock (such that no price could have been recorded).

Each price variable also comes with a set of five mutually exclusive and exhaustive dummy variables that indicate the main source of the price data in a given month (S_{0-4}^A and S_{0-4}^L). Regarding P^A , the variable S_0^A takes value 1 if most of the daily prices in the given month are directly available from *Keepa*, the variable S_1^A takes value 1 if most of the daily prices in the given month come from the in-stock Amazon prices with some out-of-stock prices imputed with Amazon prices, the variable S_2^A takes value 1 if most of the daily prices in the given month come from the in-stock Amazon prices with some out-of-stock prices imputed with List prices, the variable S_3^A takes value 1 if most of the daily prices in the given month come from the out-of-stock Amazon prices, and the variable S_4^A takes value 1 if most of the daily prices in the given month come from the out-of-stock List prices. We perform the mirror operation for the S_{0-4}^L dummies. These variables will be used as controls in the regression analysis. In Appendix Table A.2, we report the prevalence of each price source at some relevant points in time. We find no particular pattern between the source dummies and the expiry event. Consequently, we are confident that the imputation method does not affect the validity of the estimates.

Figure 2 depicts the distributions of the variables P^A and P^L . To generate this figure, we pooled together the monthly prices across all time periods for each product-patent pair. The distributions of both price series largely overlap. On average, a product in our sample costs \$221 (minimum of \$2, median of \$270 and maximum of \$14,985).

Figure 2: Distributions of log of average product prices



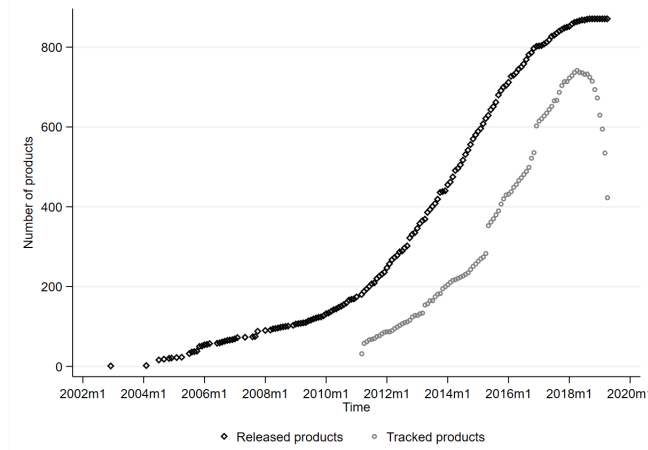
Product release date and new generation of product

We collected data on the product's release date as well as on the introduction of a new generation of product.

The product release date allows us to control for the product's age (variable *ProdAge*, in months), thereby accounting for the natural decline in price over time. The release date is set equal to the date at which the product was first available on the Amazon website or, if the information was missing, to the date of the first product review on the website. If no review is available, we set the release date equal to the date of the earliest sign of commercialization we could find online about that product.

The first product released in our data can be traced back to 2002, followed by the successive introduction of products to the market until late 2018, as shown in Figure 3. These products were first tracked by *Keepa* in March 2011 and last observed in April 2019. The number of products tracked by *Keepa* keeps growing until it peaks in early 2018. It then drops as products eventually exit the market.

Figure 3: Products having been released vs. products tracked by *Keepa*



Notes: The ‘released products’ series indicates the number of products having been released up to a given month (cumulative variable). The ‘tracked products’ series indicates the number of products tracked by *Keepa* in a given month.

We consider a new product generation as one with improved functionalities and/or designs built on the original product model. As an example, Logitech launched the original portable wireless speaker Ultimate Ears ‘UE BOOM’ in 2013 and a second-generation model ‘UE BOOM 2’ in 2015. One of the extended functionalities of UE BOOM 2 is its waterproofness (vs. the water-resistance of UE BOOM), which is protected by an additional patent, numbered US-9736560-B2.¹⁶

When a firm launches a new generation of a product, it may decide to adapt the price of the older generation. Since patent expiry may coincide with—or even trigger—new product introduction, the regression model controls for the availability of new products. We searched on Amazon.com and on other online resources for new product introduction. The dummy variable *NewGeneration* takes value 1 when a new product generation becomes available, and value 0 as long as no new product generation exists.

Competitive pressure

We propose two measures of product market competition. The first measure (*Substitutes*) captures the number of alternative products of similar functionality sold by competitors.

¹⁶Please refer to <https://www.cnet.com/reviews/ue-boom-2-review>, last accessed December 1st, 2024.

The second measure (*Competitors*) captures the number of competing firms selling substitute products (see, e.g., [Bresnahan and Reiss, 1991](#)).

We identify substitute products manually using Amazon’s recommendation algorithm, which presents a menu of relevant items on the landing page of each product. This algorithm lists relevant products that a potential buyer might be interested in based on product similarity and the purchasing behavior of customers.¹⁷ However, the algorithm itself does not distinguish complementary products from substitute ones when offering recommendations. For instance, a search for a Philips electric toothbrush returns not just electric toothbrushes from its rivals, but also toothbrush heads or toothbrush holders. We went through the list of all recommended items manually and only considered products that serve similar functional purposes as substitutes for the target products. When a product was clearly in a different price range, we did not consider it.

We have also collected data on users’ product rating on Amazon, which ranges between 1 star (lowest) and five stars (highest). Only registered users who have bought the product can submit their own rating, ensuring the quality of the information. We collected the aggregate rating directly on Amazon.com website.¹⁸

Overview of product-level variables

Table 3 provides descriptive statistics for all product-level variables. The unit of observation is a product-patent pair in a given month ($N = 491,336$). In our sample, the log of imputed monthly Amazon price (P^A) ranges from -4.61 to 10.22 with a mean of 5.39 (which corresponds to \$219). The variable P^L ranges from 0.43 to 10.22, with a mean of 5.44 (or \$230). Product age (variable *ProdAge*) counts the number of months between the product launch date and month t . It ranges from one month to 187 months (15.5 years) with a mean of 50 months. On average, 23 percent of the product-patent pairs are observed while an upgraded model is available on the market. In addition, a product

¹⁷For an explanation of Amazon’s product recommendation method, please refer to <https://www.mageplaza.com>, last accessed on March 4th, 2024.

¹⁸We collected the rating score data close to two years after the original data. Since Amazon.com updates product ASINs frequently, we only obtained rating score for 660 products in the sample.

faces an average of 15 substitutes with a maximum of 59 and a minimum of zero. The mean number of competitors in the same market segment is six, with a maximum of 30 and a minimum of zero. Finally, products in the sample have fairly high Amazon review scores; the mean value is 4.17 on a scale of 1 to 5.

Table 3: Summary statistics for product-level variables

	Mean	Standard deviation	Max	Min
$\log(\text{imputed Amazon price})$	5.42	1.55	10.22	-4.61
$\log(\text{imputed List price})$	5.44	1.44	10.22	0.43
Product age (in months)	49.46	31.42	187	1
New generation	0.23	0.42	1	0
No. of substitutes	15.03	15.94	59	0
No. of competing firms	6.32	5.84	30	0
Amazon review score	4.17	0.56	5	1
Month	-	-	2011. m3	2019. m4

4.3 Data on patents

We collected information on patents from three sources: the USPTO Patent Maintenance Fee Events dataset, PatentsView.org, and the Patent Claims Research dataset.¹⁹ We considered two types of patents, namely utility patents and design patents. A ‘utility patent,’ sometimes called an invention patent, protects the way an article is used and works (its technical aspects), whereas a ‘design patent’ protects the way an article looks (its aesthetic aspects).

Patent expiry

Our variable of interest is a dummy variable that takes value 1 when the patent has expired, and 0 if the patent is still active (*Expired*). Expiration occurs when the patent has reached its maximal statutory life. According to the USPTO Manual of Patent Examining Procedure, design patents have a 15-year term limit from the grant date if filed as of May 13th, 2015, and a 14-year term limit if filed prior to that. No renewal fee

¹⁹The data are available on <https://www.uspto.gov>, last accessed on December 1st, 2024.

is required for designs to be held active. Therefore, a design patent is expired when the statutory term limit is reached.

The case of utility patents is more complex: utility patents filed as of June 8th, 1995, have a term limit of 20 years from the patent priority date; for patents filed prior to that date, the patent term limit is either 20 years from the filing date or 17 years from the issue date, whichever is longer. Renewal fees are charged at three points in time: the fourth year, the eighth year, and the twelfth year after patent grant. A utility patent is active until the due date of the next payment, or at the termination of term if renewed at the twelfth year. Therefore, a utility patent is expired when all the renewal fees are paid, as indicated in the Patent Maintenance Fee Events dataset, and when the statutory term limit is reached. We note that it is possible that a firm may attempt to extend the market exclusivity for some products by securing additional patent protection at the end of the first patent expiry as a strategy to retain profits, a practice known as evergreening. However, as far as we know, this practice is generally limited to pharmaceutical firms (Gaudry, 2011; Hemphill and Sampat, 2012).

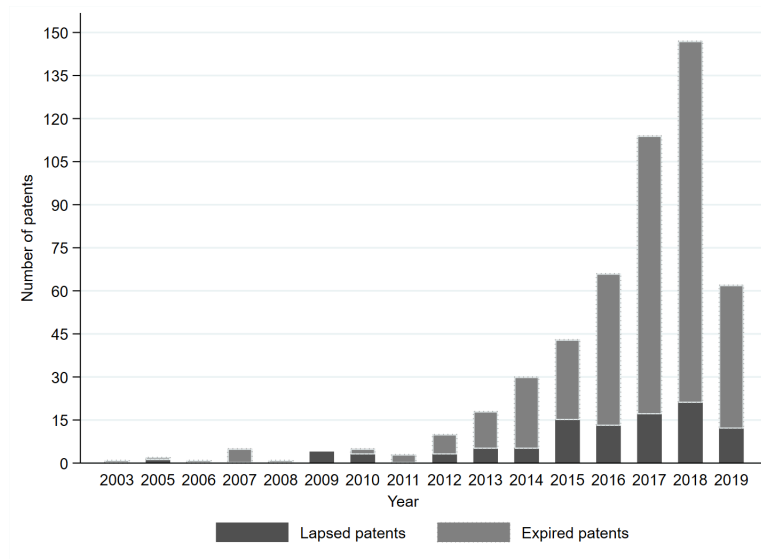
Recall that we do not exploit patents that lapse (which arise due to failure to pay the renewal fees). This is because the decision to let a patent lapse is driven, among others, by market consideration; it is likely to be endogenous to the price of the underlying product. By contrast, patent expiry after full term is clearly exogenous—there is nothing the firm can do to prolong patent life.²⁰

Figure 4 provides a breakdown of the number of lapsed vs. expired patents in our sample. Overall, 99 patents lapsed and 394 patents expired in the period from 2003 to 2019 (the remaining 2285 patents remained active throughout the study period). Additional analysis (not reported) indicates that patent lapses occur predominantly in products that build on a large number of patents—unsurprisingly so, because the importance of any single patent presumably decreases as the number of patents protecting a product becomes larger. In a robustness test, we find that excluding lapsed patents from the

²⁰To be precise, a patent’s term can be extended under certain circumstances, for example, in case of delays in the examination. There are 22 patents with an extended expiration term in our sample. Adjusting the term for these patents or excluding them from the sample does not affect our results.

sample leads to similar results.²¹

Figure 4: Distribution of lapsed and expired patents



As mentioned earlier, the key date to determine patent expiry is the priority filing date, which, roughly speaking, corresponds to the first date at which the invention is disclosed through the patent system.²² Combining the priority filing date and the product release date provides us with an estimate of the age of inventions at the time they reach the market. The left-hand side of Figure 5 depicts the number of days elapsed between the patent priority date and the release date of a focal product protected by that patent. When a patent covers more than one product, we select the earliest released product. On average, it takes 6.7 years for a patented *invention* to be commercialized into a *product* in our sample, with a mode at about two years.

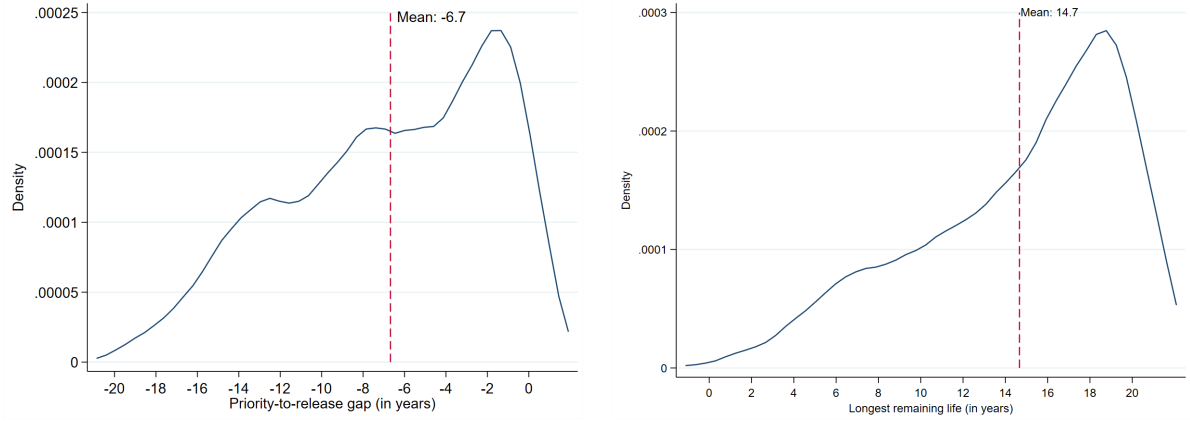
The right-hand side of Figure 5 depicts the distribution of the longest remaining time period for which a product enjoys patent protection. It is counted as the number of days between the product release date and the last maximum expiry date among all patents protecting the product. On average, a product will be protected by at least one patent for a maximum of 14.7 years in our sample—thus, far less than the 20 years of

²¹Results are available upon request from the authors.

²²According to AIA 35 U.S.C. 102(b)(1), an invention has a one-year grace period before the effective filing date during which disclosure in the form of public use or sale does not render the invention part of the prior art. In other words, inventions disclosed to the public must be submitted to the USPTO no more than 12 months after public disclosure to remain patentable. Refer to <https://www.uspto.gov> for more information, last accessed on December 1st, 2024.

statutory monopoly protection. As far as we can ascertain, it is the first time that such statistics have been reported in the literature.

Figure 5: Density of priority-to-release gap (left) and longest remaining patent life (right)



Notes: Left panel: we removed 252 out of 2778 observations whose patent priority date exceeds product release date by more than one year and 24 observations for which the product is released 20 years after the patent priority date. Right panel: we removed one observation for which the product is released 20 years after patent priority date and 125 out of 825 observations for which the last maximum expiry date exceeds 21 years after the product release date, considering the one-year grace period of patent filing.

Other patent-level variables

We collected additional patent-level variables in order to capture the ‘quality’ of patents (Lerner, 1994; Harhoff et al., 1999; Hall et al., 2005; Marco et al., 2019). We rely on ten ‘quality’ indicators constructed from Google Patents Public Datasets to evaluate how important a focal patent is.²³ These indicators of patent importance include the number of inventors, the number of assignees, the number of words in the first claim, the number of independent claims, the geographical family size, the INPADOC family size, the count of non-patent literature, patent originality, and the number of forward citations in a three-year window.

Patents in the sample form a highly-selected set of patents. To put the above indicators in perspective, we benchmark them against values obtained from a random set of 100 patents in the same IPC 4-digit class filed in the same time period (three-year window) of the focal patent. We do so for each patent in the sample, and we then count,

²³The BigQuery code developed to build the indicators is available upon request from the authors.

for each patent, the number of indicators that are above the top 20th percentile and the top 5th percentile for the relevant distribution. Thus, a patent with a score of x is one for which x out of ten indicators exceed the 20th (or 5th) percentile of their respective distributions. Besides these traditional indicators, we also evaluate the importance of a patent by the number of products it protects.

Overview of patent-level variables

Table 4 provides descriptive statistics for all patent-level variables. In our sample ($N = 491,336$), about 14 percent of product-patent pairs are observed after a patent has expired. Design patents are relatively rare, comprising about 5 percent of the observations. We also present the statistics for the set of indicators of patent importance for utility patents. For example, the three-year forward citations count for patents in our sample varies from zero to 141, averaging 7.76. The number of IPC classes for patents in our sample varies from 1 to 41, with a mean of 4.08. The number of independent claims varies from 1 to 51, with a mean of 3.48. On average, about 4 indicators (in a maximum of ten) fall in the top 20th percentile and 1.26 fall in the top 5th percentile. Last but not least, a patent on average protects 33 products with a maximum of 97 products and a minimum of one. (The apparent difference with the median number reported in Table 2 arises from the skewed distribution of the variable.)

Table 4: Summary statistics for patent-level variables

	Mean	Standard deviation	Max	Min
Expired	0.14	0.34	1	0
Design	0.05	0.22	1	0
Number of inventors	3.75	4.18	29	0
Number of assignees	1.01	0.18	8	1
Number of IPC classes	4.08	5.93	41	1
Number of independent claims	3.48	2.62	51	1
Geographic family size	5.97	5.49	34	1
INPADOC family size	75.18	181.42	720	1
Non-patent literature count	16.36	50.63	718	0
Originality	0.90	0.13	1	0
Three-year forward citations	7.76	10.24	141	0
Number of words in the first claim	175.04	104.49	1017	16
Top 20 percentile	4.06	1.93	10	0
Top 5 percentile	1.26	1.42	10	0
Products per patent	32.78	37.21	97	1

5 Econometric results

5.1 The effect of patent expiry on product prices

Table 5 presents results for the baseline specification following equation (1). Columns (1)–(3) control for product-patent pair fixed effects, whereas columns (4)–(6) control for product and patent fixed effects separately. The dependent variable is the log of Amazon price (P^A).

In column (1), we only control for product-patent pair fixed effects. The coefficient associated with the variable of interest reaches -0.149, meaning that the price is about 15 percent lower when the product loses patent protection. However, as explained previously, this figure may be inflated due to the natural decline in price over time. The regression results in column (2) controls for product age as well as for the availability of a new generation of the product.²⁴ The coefficient of interest drops to -0.111. Finally, column

²⁴To account for the possibility that prices fall at an accelerating rate with age, we have also estimated the regression model with individual month and year dummies for product age. We obtain very similar results, see columns (3) and (4) of Table A.4.

(3) controls for month dummies as well as the sources of price imputation to absorb noise from seasonal sales and variable construction. On average, product prices decline by 9.9 percent after patent expiry, *ceteris paribus*. Results in columns (4)–(6) are quantitatively similar. The coefficient of interest settles to 8.5 percent in column (6).

In our view, a 8–10 percent drop in price due to patent expiry is a rather large effect. Indeed, innovative firms usually secure their product market position using multiple strategies besides patent protection (including, e.g., branding and advertising), which helps mitigate the price decline. Furthermore, patents expire fairly late in the product life cycle, presumably when markup has already eroded significantly. To put the 8–10 percent figure in perspective, it is substantially larger than comparable estimates obtained on branded drugs. (However, in the case of drugs, customer loyalty has been shown to play a significant role in maintaining price levels post patent expiry.)

Table 5: The effect of patent expiry on product prices, baseline specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.149*** (0.010)	-0.111*** (0.011)	-0.099*** (0.010)	-0.128*** (0.008)	-0.095*** (0.009)	-0.085*** (0.008)
Product age (in months)		-0.001*** (0.000)	-0.002*** (0.000)		-0.001*** (0.000)	-0.002*** (0.000)
New generation		-0.241*** (0.019)	-0.232*** (0.017)		-0.241*** (0.019)	-0.232*** (0.017)
Month dummies	No	No	Yes	No	No	Yes
Control for price sources	No	No	Yes	No	No	Yes
Pair FE	Yes	Yes	Yes	No	No	No
Patent FE	No	No	No	Yes	Yes	Yes
Product FE	No	No	No	Yes	Yes	Yes
Constant	5.385*** (0.001)	5.485*** (0.012)	5.515*** (0.008)	5.382*** (0.001)	5.485*** (0.012)	5.514*** (0.008)
No. products	825	825	825	825	825	825
No. patents	2,778	2,778	2,778	2,778	2,778	2,778
No. pairs	14,621	14,621	14,621	14,621	14,621	14,621
Observations	491,336	491,336	491,336	491,336	491,336	491,336
R-squared	0.899	0.900	0.901	0.899	0.900	0.901

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table 6, we present estimates obtained using the List price as the dependent variable (P^L), following the same structure as in the previous table. Patent expiry results in a 7.9–9.4 percent drop in list prices in columns (3) and (6), which is qualitatively similar to the baseline estimates. In the remainder of the analysis, we present estimates obtained

with the Amazon price variable, but we note that all results are robust to the use of the List price variable.

Table 6: The effect of patent expiry on product prices, alternative price variable

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.233*** (0.017)	-0.113*** (0.018)	-0.094*** (0.018)	-0.199*** (0.014)	-0.095*** (0.015)	-0.079*** (0.015)
Product age (in months)		-0.005*** (0.000)	-0.008*** (0.000)		-0.005*** (0.000)	-0.008*** (0.000)
New generation		-0.022* (0.013)	-0.108*** (0.009)		-0.021* (0.013)	-0.107*** (0.009)
Month dummies	No	No	Yes	No	No	Yes
Control for price sources	No	No	Yes	No	No	Yes
Pair FE	Yes	Yes	Yes	No	No	No
Patent FE	No	No	No	Yes	Yes	Yes
Product FE	No	No	No	Yes	Yes	Yes
Constant	5.467*** (0.002)	5.691*** (0.009)	5.877*** (0.012)	5.463*** (0.002)	5.690*** (0.009)	5.876*** (0.012)
No. products	825	825	825	825	825	825
No. patents	2,778	2,778	2,778	2,778	2,778	2,778
No. pairs	14,621	14,621	14,621	14,621	14,621	14,621
Observations	499,193	499,193	499,193	499,193	499,193	499,193
R-squared	0.960	0.962	0.965	0.960	0.962	0.965

Notes: Dependent variable is $\log P_{ijt}^L$. Standard errors clustered at the patent level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Since prices go down following patent expiry, it is likely that markups decrease, resulting in a drop in profit per unit sold. We cannot test this assertion directly because we do not observe markups. However, following [Bils \(2016\)](#), we use stockout frequency as a proxy for markup. [Bils \(2016\)](#) shows that markup is negatively related with stockout, simply because stockouts are more costly to the firms for high-markup products. Accordingly, Table 7 uses the inventory out-of-stock frequency from Amazon as a proxy for markups and replicates the baseline model. Estimates in columns (3) and (6) show an 11.8–13.8 percent increase in the out-of-stock frequency following patent expiry.²⁵ This result offers an alternative, non-price-based evidence on patent expiry and markups.

²⁵Note that the negative (and statistically insignificant) coefficient on the variable Expired in columns (1) and (4) reflects the omission of Product age as a control.

Table 7: The effect of patent expiry on stockout frequency

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.287 (0.227)	0.708*** (0.253)	0.138* (0.078)	-0.247 (0.196)	0.604*** (0.215)	0.118* (0.066)
Product age (in months)		-0.046*** (0.004)	-0.025*** (0.001)		-0.046*** (0.004)	-0.025*** (0.001)
New generation		1.793*** (0.197)	-0.129* (0.066)		1.792*** (0.197)	-0.129* (0.067)
Constant	4.034*** (0.031)	5.768*** (0.188)	2.954*** (0.192)	4.029*** (0.026)	5.770*** (0.188)	2.955*** (0.192)
Observations	491,336	491,336	491,336	491,336	491,336	491,336
R-squared	0.373	0.377	0.878	0.373	0.377	0.878
Month dummies	No	No	Yes	No	No	Yes
Control for price sources	No	No	Yes	No	No	Yes
Pair FE	Yes	Yes	Yes	No	No	No
Patent FE	No	No	No	Yes	Yes	Yes
Product FE	No	No	No	Yes	Yes	Yes

Notes: The dependent variable is monthly stockout frequency. Standard errors clustered at the patent level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We have performed additional robustness checks, which we report in Appendix Table A.3. We control for product age $\times$ product category fixed effects to account for different time trends across product types. We also control for calendar year fixed effect to capture macro trends that may affect product price. Finally, we control for the one-year lagged price to capture unobserved dynamic product-level factors. We control for product-patent pair fixed effects in columns (1)–(3) and for product and patent fixed effects in columns (4)–(6). These alternative specifications all confirm the robustness of the main result, with the coefficient of interest ranging between 5.6 and 9.3 percent.

The novelty requirement in patent law imposes all patents protecting a product to be filed at the latest one year after the product launch date. (If the invention has been disclosed for too long before a patent application is filed, it is no longer considered patentable.) Thus, in theory, we should not observe patent applications with a priority date that exceeds the product launch date by more than twelve months. Yet, we do have such cases in our data, either because of a mistake by the firm or because we have inaccurately collected the product launch date. Table A.4 assesses the sensitivity of the findings to these mistakes. In column (1), we exclude products whose launch date exceeds the one-year grace period limit. In column (2), we edit the product launch date

by shifting it to exactly one year before the latest patent priority date for problematic cases—thereby altering the product age. In columns (3) and (4), we estimate baseline specifications with product age dummy variables in months and in years. The effect of patent expiry is consistent and similar to our baseline estimate, ranging from 9.8 to 12.6 percent under these specifications.

Accounting for patent type and importance

So far, we have bundled together design patents and utility patents, even though they protect different features of a product and have a differentiated legal treatment. In Table 8, we split the sample by patent type. It clearly appears that prices react to the expiry of utility patents (columns 1–2) on a similar level to the baseline estimate. The expiry of design patents (columns 3–4) does not seem to affect prices.

The lack of effect for design patents does not necessarily mean that design rights are worthless. The visual and ornamental features of a product contribute to its positioning and, hence, to its price ([Eisenman, 2013](#)). The lack of effect may suggest that these decorative features may continue to uniquely identify the product even after the design rights have expired, which helps to sustain higher markups. This mechanism would be similar to that observed on drugs, where the brand name helps to sustain high drug prices after patent expiry.

Table 8: The effect of patent expiry on product prices by patent type

	(1)	(2)	(3)	(4)
	Utility patents		Designs	
Expired	-0.104*** (0.010)	-0.099*** (0.009)	0.019 (0.017)	0.013 (0.022)
Product age (in months)	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
New generation	-0.237*** (0.018)	-0.247*** (0.020)	-0.122*** (0.033)	-0.110*** (0.036)
Month dummies	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes
Pair FE	Yes	No	Yes	No
Patent FE	No	Yes	No	Yes
Product FE	No	Yes	No	Yes
Constant	5.571*** (0.008)	5.547*** (0.013)	4.515*** (0.020)	4.394*** (0.017)
No. products	745	745	285	285
No. patents	2,417	2,417	361	361
No. pairs	14,055	14,055	566	566
Observations	466,331	466,331	25,005	25,005
R-squared	0.894	0.893	0.986	0.986

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

There is a large amount of heterogeneity in patent value. As [Lemley and Shapiro \(2005, p. 85\)](#) put it, “many patents are virtually worthless,” either because they cover technology that is not commercially viable, because they are impossible to enforce effectively, or because they are very unlikely to hold up in court if litigated. However, “a small number of patents are of enormous economic significance.” Patents in our sample form a highly selected set of inventions that are commercially relevant and, in all logic, more valuable than the average U.S. patent. Nevertheless, patents in our sample also exhibit heterogeneity in their value, as suggested by the ten indicators of patent importance in Table 4.

Table 9 interacts the variable of interest with indicators of patent importance. Estimates exploiting the quantile-based measures in columns (1)–(2) and (4)–(5) do not produce significant results. In other words, we do not observe that product prices react to the metrics of patent importance traditionally used in the literature. However, the

expiry of ‘key’ patents, protecting a large number of products, exacerbates the decline in prices, as indicated in columns (3) and (6). This result is consistent with a competitive pressure hypothesis, with the expiry of key patents representing a greater risk to innovative firms.

Table 9: The effect of patent expiry on product prices by patent importance

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.119*** (0.018)	-0.096*** (0.012)	-0.054** (0.021)	-0.095*** (0.014)	-0.082*** (0.010)	-0.054*** (0.020)
Expired × Top 20 percentile	0.005 (0.005)			0.003 (0.004)		
Expired × Top 5 percentile		-0.008 (0.008)			-0.006 (0.006)	
Expired × $\log(\text{Products per patent})$			-0.015*** (0.006)			-0.010** (0.005)
Product age (in months)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
New generation	-0.237*** (0.018)	-0.237*** (0.018)	-0.237*** (0.018)	-0.237*** (0.018)	-0.237*** (0.018)	-0.237*** (0.018)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	No	No	No
Patent FE	No	No	No	Yes	Yes	Yes
Product FE	No	No	No	Yes	Yes	Yes
Constant	5.568*** (0.008)	5.568*** (0.008)	5.569*** (0.008)	5.568*** (0.008)	5.568*** (0.008)	5.568*** (0.008)
No. products	745	745	745	745	745	745
No. patents	2,413	2,413	2,413	2,413	2,413	2,413
No. pairs	13,971	13,971	13,971	13,971	13,971	13,971
Observations	464,019	464,019	464,019	464,019	464,019	464,019
R-squared	0.894	0.894	0.894	0.894	0.894	0.894

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Design patents excluded from the sample. Please Note that 4 utility patents are discarded because of incomplete information.

Product-level estimates

Thus far, our analysis has exploited the many-to-many relationship between patents and products by operating at the patent–product level. This approach enables us to estimate the average effect of patent expiration and examine heterogeneity across patents. However, it rests on two key assumptions.

First, it implicitly treats the effect of losing patent protection as independent of the total number of patents covering a product. In other words, it assumes that the loss of protection on a single-patent product has the same impact as the expiration of one patent

among many.

Second, it assumes that each patent expiration is an independent treatment event—even when multiple patents linked to the same product expire simultaneously and jointly drive the observed price change. This can lead to an upward bias in our estimates of the effect of patent expiration.²⁶

In this section, we adopt an alternative estimation strategy, using the product as the unit of analysis. When two or more patents protect a product, the *Expiry_{it}* variable is a continuous variable defined on the [0,1] interval capturing the proportion of patents expired at time t .²⁷ Columns (1)–(3) of Table 10 report the estimates for multi-patent products only, whereas columns (4)–(6) consider all products. We find that product prices decline by 0.34–0.56 percent with a ten percentage point increase in the proportion of expired patents.

Table 10: Product-level regression on the effect of patent expiry

	(1)	(2)	(3)	(4)	(5)	(6)
	Products with more than one patent			All products		
Expired	-0.110*** (0.025)	-0.061** (0.027)	-0.056** (0.027)	-0.091*** (0.016)	-0.040** (0.018)	-0.034* (0.018)
Product age (in months)		-0.002*** (0.000)	-0.002*** (0.000)		-0.001*** (0.000)	-0.002*** (0.000)
New generation		-0.173*** (0.042)	-0.180*** (0.041)		-0.167*** (0.040)	-0.180*** (0.039)
Month dummies	No	No	Yes	No	No	Yes
Control for price sources	No	No	Yes	No	No	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.488*** (0.004)	4.583*** (0.018)	4.626*** (0.029)	4.042*** (0.003)	4.132*** (0.014)	4.175*** (0.023)
Number of Products	602	602	602	825	825	825
Observations	23,541	23,541	23,541	35,898	35,898	35,898
R-squared	0.982	0.982	0.983	0.983	0.984	0.984

Notes: The dependent variable is $\log P_{ijt}^A$. Because the sample is compressed at the product level, standard errors are clustered at the product level. *** p<0.01, ** p<0.05, * p<0.1.

²⁶That said, this potential bias is likely limited in practice: only a small share of patent–product observations (1,433 out of 10,622) involve multiple patents expiring in the same month for the same product.

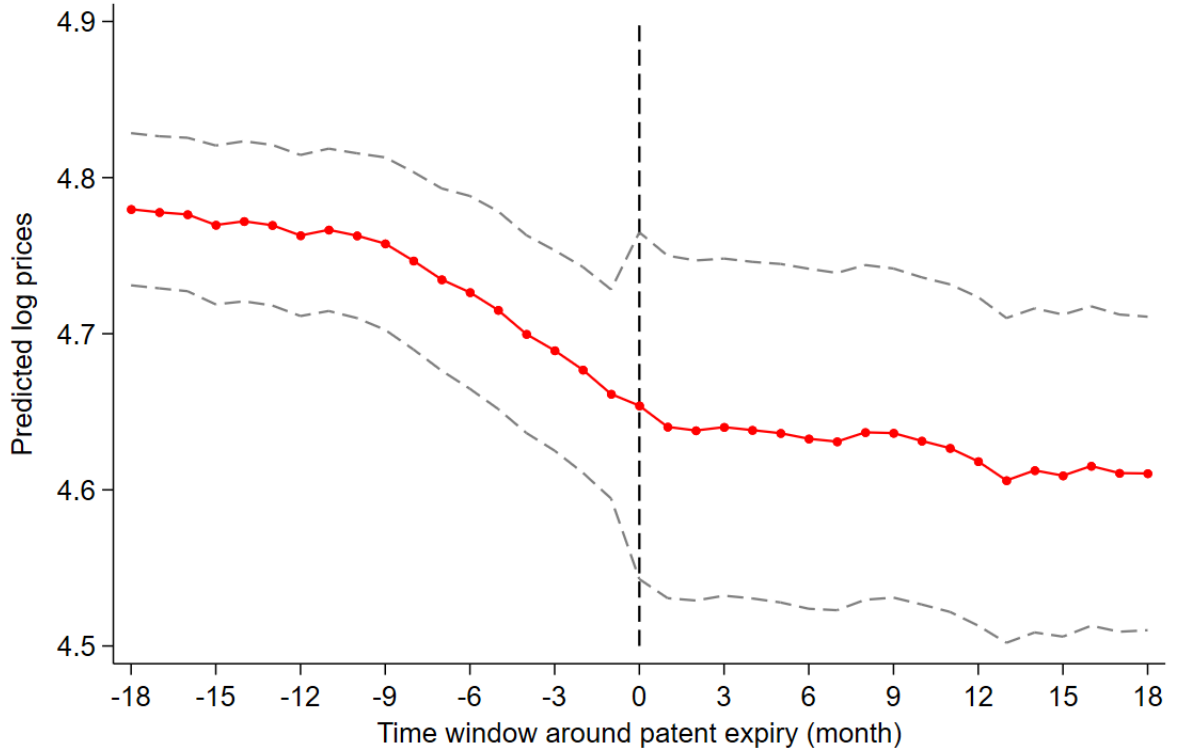
²⁷The mean of *Expiry_{it}* is 0.14 and the standard deviation is 0.34.

Temporal effect

This section explores the temporal dimension of the price decline, intending to shed light on the underlying mechanism. We use an event-study method and restrict our sample to observations that fall into an 18-month time window before and after patent expiry. We add a dummy variable for each leading/lagging month around patent expiry to our baseline model (presented in column 3 of Table 5). We then recover and plot the predicted log price from the regression coefficients. The result, shown in Figure 6, indicates that the decline in prices starts about one year prior to patent expiry despite a general downward trend in product prices due to product aging or displacement. It then seems to stabilize shortly after patent expiry.

The gradual price decline observed in this event study suggests that our main estimates at the monthly level may be attenuated due to anticipatory behavior and, therefore, provide a conservative estimate of the effect of patent expiry on product prices. Using the data from Figure 6, the drop in predicted prices over the ten months that precede expiry reaches about 10.40 percent $(e^{4.76} - e^{4.65})/e^{4.76}$.

Figure 6: Evolution of product prices around patent expiry



Notes: The sample is restricted to product-patent pairs that are either active or expired. The dashed lines depict the upper and lower bounds of the 95-percent confidence interval.

We see two possible reasons for the effect. First, it could result from strategic entry deterrence by the incumbent ([Milgrom and Roberts, 1982](#); [Smiley, 1988](#); [Scott Morton, 2000](#); [Goolsbee and Syverson, 2008](#); [Tenn and Wendling, 2014](#)). This strategy has been observed in the airline and pharmaceutical industries, where the incumbent proactively reduces the price to lower market attractiveness for would-be competitors. In fact, considering that products in the sample are durable goods, lowering the price shortly before patent expiry could be a rational strategy, even without any intention to deter entry. It allows the incumbent to capture a greater share of consumers, removing them from the set of prospective buyers. Second, competitors might enter the market shortly before patent expiry, betting that the incumbent will not start a costly and lengthy infringement case. This explanation is consistent with [Love \(2012\)](#), who reports that product-producing companies enforce their patents soon after issuance—seldom litigating them near the end of their lives. In the absence of a time-varying competition variable (discussed below),

we are left with conjectures.

5.2 Accounting for product market competition

So far, we have established that product prices react negatively to patent expiry. The price drop is more significant for more important patents and starts about one year before the actual expiry. In this section, we test the extent to which the price drop reacts to product market competition.

5.2.1 An index of competitive pressure

A limitation of the data is that we cannot observe when a substitute product is launched or when a competitor enters the market. But we have information on the number of substitutes at the time of data collection, which we use to proxy product-level market competition. Thus, we should think of our measure as an index of competitive pressure rather than as a fine-grained observation of competition. We build two indices: the number of similar products sold by competitors (*Substitutes*) and the number of competing firms selling the substitutes (*Competitors*).

To examine how market competitiveness moderates the effect of patent expiry, we interact the patent expiry event with each of the competition measures as well as their squared terms. Columns (1)–(4) of Table 11 report estimates with the product-patent fixed effect and columns (5)–(8) with patent and product fixed effects. We find that, by and large, the intensity of competition exacerbates the effect of patent expiry on price.²⁸ However, the squared terms are positive and statistically significant, suggesting a U-shaped relationship.

Figure 7 depicts the non-monotonic effect of competition on price using the models in columns (2) and (4). It also reports the distribution of substitute products and competitors in the sample. The existence of a U-shaped relationship makes intuitive sense.

²⁸We do not claim that the relationship is causal. Market structure is a highly endogenous object influenced by some of the same factors that impact price changes.

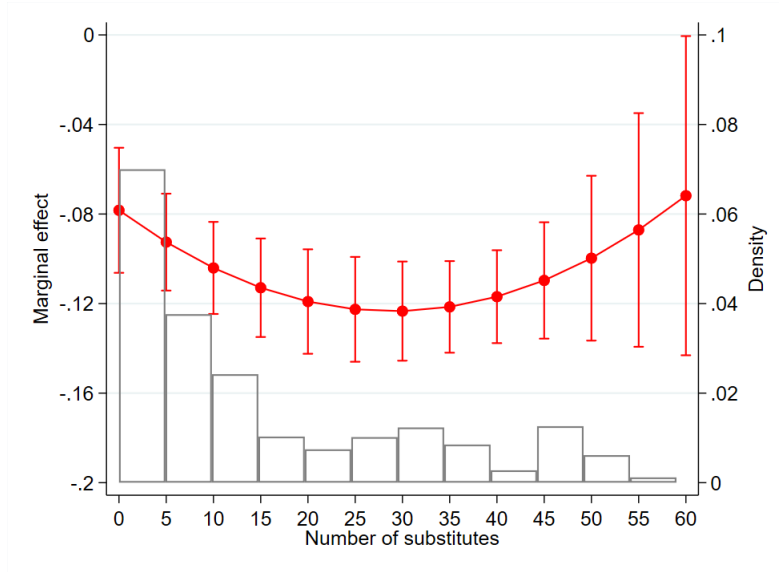
In markets with no-to-limited competitive pressure, the effect of patent protection must be limited. As competitive pressure increases, patent protection becomes more valuable to the firm. However, as competition increases further, competitors may develop substitute technologies or may invent around the patent to render the patent protection virtually useless. Having noted this, most observations fall in the downward-sloping part of the effect, meaning that competition usually exacerbates the pressure on prices. In our sample, the maximum drop in prices occurs for products facing 30 substitutes and ten competitors.

Table 11: Patent expiry and competition

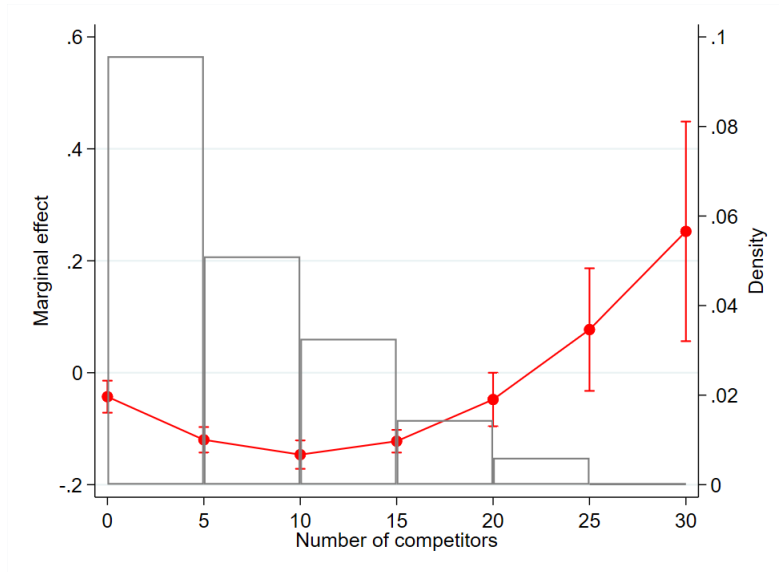
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expired	-0.090*** (0.012)	-0.078*** (0.014)	-0.081*** (0.012)	-0.043*** (0.015)	-0.082*** (0.008)	-0.078*** (0.009)	-0.079*** (0.008)	-0.069*** (0.008)
Expired $\times$ Substitutes	-0.001* (0.000)	-0.003** (0.001)			-0.000* (0.000)	-0.001*** (0.000)		
Expired $\times$ Substitutes ²		0.000* (0.000)				0.000** (0.000)		
Expired $\times$ Competitors			-0.003*** (0.001)	-0.020*** (0.004)			-0.001*** (0.000)	-0.006*** (0.001)
Expired $\times$ Competitors ²				0.001*** (0.000)				0.000*** (0.000)
Product age (in months)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
New generation	-0.231*** (0.017)	-0.231*** (0.017)	-0.231*** (0.017)	-0.230*** (0.017)	-0.232*** (0.017)	-0.231*** (0.017)	-0.231*** (0.017)	-0.231*** (0.017)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes	No	No	No	No
Patent FE	No	No	No	No	Yes	Yes	Yes	Yes
Product FE	No	No	No	No	Yes	Yes	Yes	Yes
Constant	5.515*** (0.008)	5.515*** (0.008)	5.514*** (0.008)	5.514*** (0.008)	5.514*** (0.008)	5.514*** (0.008)	5.514*** (0.008)	5.514*** (0.008)
No. products	825	825	825	825	825	825	825	825
No. patents	2,778	2,778	2,778	2,778	2,778	2,778	2,778	2,778
No. pairs	14,621	14,621	14,621	14,621	14,621	14,621	14,621	14,621
Observations	491,336	491,336	491,336	491,336	491,336	491,336	491,336	491,336
R-squared	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 7: Non-monotonic effects on price of the number of substitutes (a) and competitors (b).



(a)



(b)

Notes: 95-percent confidence intervals reported.

5.2.2 Alternative measures

In this section, we seek to shed additional light on the role of the competitive environment. We report indirect evidence that the price drop following patent expiry is more pronounced in more competitive environments.

Concretely, we estimate the impact of product ‘quality’ on the price drop, using

customer review scores as a proxy for quality (Sun, 2012). As product quality tends to be positively associated with the brand (Rao and Monroe, 1989), higher-quality products may induce consumers to be brand loyal and thus mitigate the negative effect of patent expiration amid competition. To the extent that higher-quality products are less easily substitutable than lower-quality ones, we expect a lower price decrease for better-rated products. We have no information on the Amazon review score for 165 products, and we first estimate the baseline regression model on the subsample of products with non-missing review scores for comparison purposes, see columns (1) and (3) of Table 12. The regression models in columns (2) and (4) include an interaction term between the variable *Expired* and the Amazon review score. A one-unit increase in the Amazon customer review score mitigates the price drop by about 3.0–6.5 percent, suggesting that product quality eases the competitive pressure, at least in the short term. Highest-quality products, with a five-star rating, experience a price decline of 2.2–4.1 percent on average. By contrast, medium-quality products, with a three-star rating, experience a price decline of 10.1–15.2 percent on average. This result is in line with the finding documented by Grabowski and Vernon (1992) that pharmaceutical firms with strong brand loyalty have an incentive not to cut prices.

Table 12: Patent expiry and Amazon review score

	(1)	(2)	(3)	(4)
Expired	-0.068*** (0.011)	-0.347*** (0.083)	-0.062*** (0.010)	-0.191*** (0.040)
Expired $\times$ Amazon review score		0.065*** (0.018)		0.030*** (0.008)
Product age (in months)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
New generation	-0.264*** (0.020)	-0.263*** (0.020)	-0.264*** (0.020)	-0.263*** (0.020)
Month dummies	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	No	No
Patent FE	No	No	Yes	Yes
Product FE	No	No	Yes	Yes
Constant	4.990*** (0.011)	4.991*** (0.011)	4.990*** (0.011)	4.991*** (0.011)
No. products	660	660	660	660
No. patents	2,336	2,336	2,336	2,336
No. pairs	7,878	7,878	7,878	7,878
Observations	329,543	329,543	329,543	329,543
R-squared	0.845	0.845	0.845	0.845

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2.3 Patents as a competitive advantage

It is a well-known fact that the effectiveness of patent protection varies across sectors (Cohen et al., 2000; Hall and Ziedonis, 2001; Von Graevenitz et al., 2013). It works well in some sectors (e.g., drugs), but it plays a negligible role in others. Our setup allows us to investigate the effect of patent expiry in different environments.

We identify environments characterized by weak and strong IP regimes in two ways. First, we rely on sectoral differences in the prevalence of markets for technologies. Vibrant markets for technologies indicate that IP is central to technology commercialization, and sectors with such markets naturally pay more attention to IP. For each patent in the sample, we observe which firm currently claims a right to the patent (firm V , from the VPM webpage) and which firm originally filed it (firm P , listed in the patent document).

If firm names differ, we can infer that the patent has been sold or licensed from firm P to firm V , i.e., has been the subject of a transaction on the market for technology.²⁹ Overall, we have identified 82 transacted patents, and 90 percent of the transactions are concentrated in four product categories, namely Automotive Parts, Electronics, Health & Household, and Video Games. We classify these product categories as strong IP regimes and the remaining as weak IP regimes.

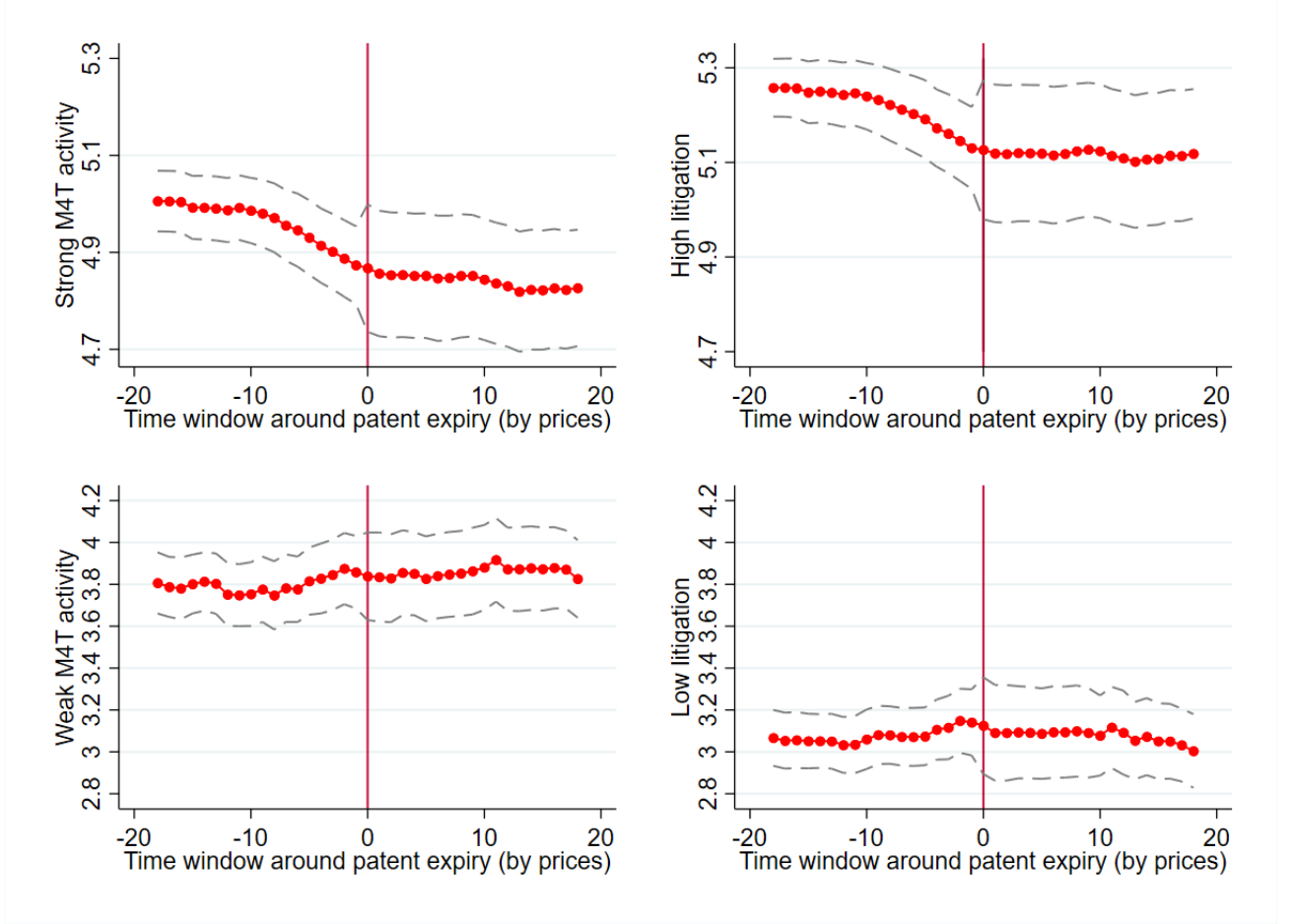
Second, we identify strong and weak IP regimes using litigation data. We were able to match 71 patents from our sample to the Stanford patent litigation dataset.³⁰ These patents are associated with 245 products. Here, products with at least one litigated patents constitute the strong IP group whereas the others products constitute the weak IP group.

Figure 8 presents the evolution of prices around patent expiry in strong and weak IP regimes. The left panels exploit transactions on markets for technologies, whereas the right panels exploit litigation data. The price drop is very visible in the top panels, which depict strong regimes. By contrast, we observe hardly any price variations in the bottom panels associated with weak regimes. This is likely because the market tends to be more competitive when the IP regime is weak to the extent that patent protection may not be effective in excluding rivals and thus generating a price premium.

²⁹An alternative explanation is that firm V has acquired firm P and its patent portfolio. In constructing our data, we account manually for the changing ownership structure of companies.

³⁰This figure implies that about three percent of patents in our sample are litigated, which is considerably higher than the prevalence of litigation in the population of U.S. patents. Considering expired patents only, 27 out of 394 patents were litigated, representing about seven percent of the sample.

Figure 8: Evolution of product prices around patent expiry by IP regime



Notes: The sample is restricted to product-patent pairs that are either active or expired. The dashed lines depict the upper and lower bounds of the 95-percent confidence interval.

5.3 Placebo tests

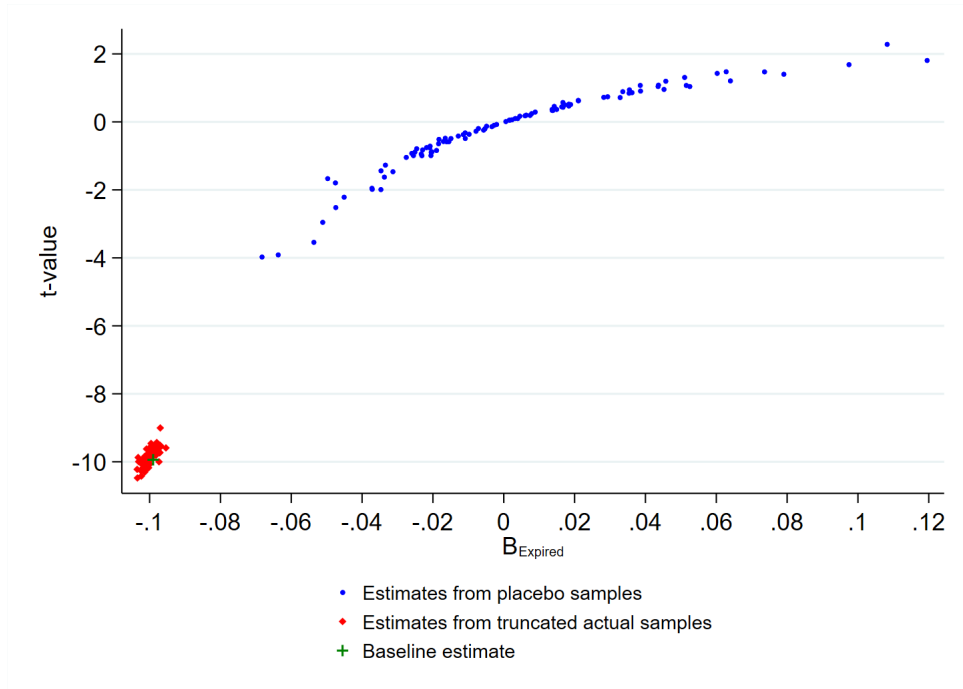
We have accounted for confounding factors that are likely to threaten the validity of our estimates, namely product age and the introduction of a new product generation (as well as the fixed effects). In this section, we implement two placebo tests to further assess the validity of our results.

The first placebo test focuses on the sample of observations associated with patents that were active throughout the study period. We create fake expiry events on a random set of these patents and re-estimate equation (1). In all logic, these fake expiry events should not have any effect on product prices. We perform 100 estimates, every time randomly assigning fake expiry dates on a randomly selected set of active patents. We

randomly select 17 percent (to mimic actual data) of the active patents and assign each of them an expiry date that is randomly and uniformly distributed between January, 2011 and April, 2019, leaving the other active patents unchanged. We plot the $\hat{\beta}$'s and the corresponding t-values associated with the placebo *Expired* variable.

Next, we want to compare the placebo $\hat{\beta}$'s with the $\hat{\beta}$ estimated with the real data. Directly comparing the two quantities would be unfair, however, because sample sizes differ. Consequently, we also estimate equation (1) using the real data, randomly dropping 28 percent of the observations—so the placebo and the real-but-truncated samples are of similar size. Figure 9 reports the estimated $\hat{\beta}$'s as well as their t-values. The coefficients estimated using the placebo samples have a mean of -0.001 and t-values that are frequently below the statistical significance threshold. By contrast, the $\hat{\beta}$'s estimated from the randomly reduced samples are scattered tightly around the baseline $\hat{\beta}$ (-0.099) and are all statistically significantly different from zero.

Figure 9: Overview of $\hat{\beta}$'s estimated from placebo tests



Notes: Estimates marked by dots come from placebo samples whereas estimates marked by diamonds come from truncated actual samples. The cross reports the $\hat{\beta}$ and t-value obtained from the baseline model as in column (3) of Table 5. See Appendix Table A.5 for underlying data.

In the second placebo test, we focus only on the sample of patents that have expired.

We assign fake expiry events *prior* to the true expiry. To ensure a similar number of observations across the various samples, we restrict the samples to product-patent pairs observed within a one-and-a-half-year time window around the actual or the placebo expiry date. We then set the placebo expiry events to two and a half years, three years, and three and a half years prior to the actual expiry month, respectively. In column (1) of Table 13, the effect of the true expiry event is statistically significant, and its magnitude is close to the baseline estimate. By contrast, the coefficients estimated on the placebo expiry events are *positive* as shown in columns (2)–(4).

The fact that the coefficients are positive may be surprising. Further checks suggest that the positive coefficients reflect non-linearities in the relationship between product age and price. Not controlling for the product age variable in columns (6)–(8) leads to insignificant coefficients for the dummy expiry events, whereas the true expiry event is associated with a strong price decrease. We conclude that, if anything, controlling for product age in the baseline specification leads to conservative estimates of the effect of patent expiry on product price. Taken together, these figures confirm that the price decline that we observe once the patent expires does not merely reflect the effect of the passing of time.

To sum up, results from the placebo tests confirm that there is a genuine price drop that occurs around the time of patent expiry—we are thus not concerned by the possibility that our empirical design might drive the results.

Table 13: Placebo test: the effect of patent expiry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expired	-0.094*** (0.018)				-0.161*** (0.014)			
Expired (2.5 years before)		0.369** (0.168)				0.136 (0.109)		
Expired (3 years before)			0.380** (0.153)				0.146 (0.108)	
Expired (3.5 years before)				0.118** (0.053)				-0.022 (0.053)
Product age (in months)	-0.002*** (0.001)	-0.007*** (0.002)	-0.006*** (0.001)	-0.004*** (0.001)				
New generation	-0.080*** (0.012)	-0.477*** (0.179)	-0.552** (0.210)	-0.267* (0.135)	-0.109*** (0.008)	-0.499*** (0.183)	-0.551** (0.209)	-0.267** (0.133)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.742*** (0.021)	4.431*** (0.085)	4.336*** (0.078)	4.170*** (0.045)	4.661*** (0.021)	4.119*** (0.051)	4.015*** (0.055)	3.972*** (0.058)
No. products	86	69	60	52	86	69	60	52
No. patents	80	96	81	70	80	96	81	70
No. pairs	325	188	156	125	325	188	156	125
Observations	18,964	12,038	10,171	8,136	18,964	12,038	10,171	8,136
R-squared	0.985	0.807	0.787	0.908	0.984	0.804	0.785	0.907

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

6 Concluding remarks

This paper provides evidence of the monopoly pricing power of patents. Specifically, it reveals a drop in the price of a sample of consumer products listed on Amazon.com around the time they lose patent protection. We find that patent expiry is associated with a 8–10 percent drop in product price. Because we measure the effect of patent expiry on market protection when market power is presumably at the weakest, i.e., quite late in the product lifecycle, the 8–10 percent figure is likely to be a conservative estimate. As far as we can ascertain, the present paper is the first to report direct evidence of a markup for patent-protected consumer products. We have achieved this result thanks to a novel way of identifying the correspondence between patents and products. The results complement earlier findings related to patent-protected drugs (Caves et al., 1991; Grabowski and Vernon, 1992; Frank and Salkever, 1997; Wiggins and Maness, 2004; Vandoros and Kanavos, 2013) as well as copyrighted books (Li et al., 2018; Reimers, 2019)—an admittedly distinct type of IP right.

The empirical analysis produces insights that inform us about the possible mechanisms at play. We observe that prices start to decline about one year before actual patent expiry. This result is consistent with a preemptive price reduction by the incumbent with a view of deterring market entry, although we note that other mechanisms may be at play. More importantly, we document that the price decline following expiry is greater in more competitive environments and in environments in which patents are known to be particularly effective. These findings provide evidence that patents protect against competition.

The econometric results also pass a long series of sanity and robustness tests. Among other tests, we find that the price drop is larger for more important patents, as proxied by the number of products that the patent protects. We also find that product prices react only to the expiry of utility patents and not design patents. Design patents do not undergo a substantive examination and, therefore, offer a weaker form of protection. Finally, the results are robust to a range of alternative specifications and placebo tests of fake expiry events.

In passing, we were also able to compute, for the first time, statistics about the link between products and patents. The median number of patents per product is four, the median number of products per patent is two, and there are wide disparities in these figures across product categories. We also found that it takes on average six and half years before a patented invention is first commercialized. The data have also allowed us to estimate that patented products *de facto* enjoy an exclusivity of maximum 15 years (i.e., until the last patent in a product expires) from the time they are first released on the market.

The policy implications of the findings are clear: patents seem to provide *some* level of protection in the product market, thereby providing evidence that the patent system helps sustain supra-competitive prices for innovators. This finding represents an important step in our understanding of the functioning of patent systems. The 8–10 percent figure sheds light on the markup enjoyed by incumbent innovators, though it is

a conservative estimate because of the proximity to patent expiry. It is a measure of the welfare loss associated with the patent monopoly described in theoretical models—or, in other words, the subsidy rate paid by consumers. However, the paper does not address the net welfare benefit (or cost) of supra-competitive pricing. Future research should find ways to observe the markup throughout the entire duration of patent life and combine it with sales data to estimate the patent premium. Such estimates should then be contrasted with the R&D cost associated with the underlying products. Only then can one quantify the magnitude of the incentive effect that the patent premium represents. There is still a long way to go before fully understanding the welfare effects of the patent system. We note that the present paper makes a step in this direction, and we hope that the data will enable follow-on research on this topic.

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A Appendix

Table A.1: A list of selected product(s) by Amazon product catalog

Amazon product catalog	Subcatalog	Firm	Representative product(s)
Appliances	Vacuum	Dyson	AM08 / DC35
Appliances	Ceiling Fans & Accessories	Emerson	CF830 MONACO FAN
Appliances	Vacuum	Kaivac, Inc.	KaiVac
Appliances	Small Appliances	NuWave Now	NuWave® Precision Induction Cooktop (Flex)
Automotive Parts	Replacement Parts	ANCO	A-14-M
Automotive Parts	Replacement Parts	Bosch	Clear Advantage 28CA
Automotive Parts	Replacement Parts	diono	Easy View Mirror
Automotive Parts	Accessories	Lippert Components	FLIP™ jack foot
Automotive Parts	Towing Products & Winches	Warn Industries	ProVantage Winches
Baby Products	Accessories	Munchkin	Bristle Brush
Baby Products	Strollers & Accessories	phil&teds	Verve Buggy
Clothing, Shoes & Jewelry	Shoes	KEEN	Yogui Arts
Clothing, Shoes & Jewelry	Shoes	Newton Running Company	Aha
Electronics	Camera & Photo	360fly	360FLYBLK
Electronics	Computers & Accessories	Advantech	EKI-2528PA1
Electronics	Cell Phones & Accessories	Belkin	F8Z442
Electronics	Cell Phones & Accessories	BlackBerry	BlackBerry® Classic
Electronics	Computers & Accessories	Brocade	Brocade NetIron CER 2000 Series
Electronics	Computers & Accessories	Cirque Corporation	Gen 3 and earlier
Electronics	Accessories & Supplies	CommScope	Cables Coaxial Braided
Electronics	Computers & Accessories	Control4	C4-TV120277
Electronics	Camera & Photo	Draper, Inc.	Micro Projector Lift
Electronics	Computers & Accessories	Elo Touch Solutions	Touch Screen
Electronics	Computers & Accessories	Honeywell	Voyager 1250g / Xenon 1900g General Duty Scanners
Electronics	Cell Phones & Accessories	HTC	HTC One (®) (E8)
Electronics	Computers & Accessories	Kent Displays	Boogie Board™ Original 8.5 eWriter
Electronics	Television & Video	KING Connect	Tailgater® VQ2500
Electronics	Computers & Accessories	Logitech	Logitech G603 Mouse / Logitech K811 Keyboard
Electronics	Computers & Accessories	Mad Catz	Mad Catz V.7 Keyboard
Electronics	Computers & Accessories	Neonode	Neonode AirBar® sensor
Electronics	Computers & Accessories	Okidata Americas, Inc.	ES3640e MFP
Electronics	Headphones	Skullcandy Inc.	Soundmine
Electronics	Portable Audio & Video	Sonos, Inc.	One
Electronics	Television & Video	Sound United	AV Receiver AVR-4520
Electronics	Computers & Accessories	tyconsystems	Tycon Systems 802.3at
Electronics	Camera & Photo	X-Rite	331C
Health & Household	Beauty & Personal Care	CND	Radical SolarNail™
Health & Household	Medical Supplies & Equipment	Game Ready	Straight Knee Wrap
Health & Household	Beauty & Personal Care	Kao Corporation	Jergens® Shea Butter
Health & Household	Household Supplies	Kimberly-Clark	COTTONELLE® CleanCare Toilet Paper
Health & Household	Household Supplies	Procter & Gamble	Power Razor
Health & Household	Household Supplies	RB	FINISH Powerball Quantum Max Capsules Ultra Degreaser
Industrial & Scientific	Industrial Electrical	American Radionic	Turbo® 200
Industrial & Scientific	Building Supplies	CleanAlert	FILTERSCAN WiFi (FS-245-C)
Industrial & Scientific	Additive Manufacturing Products	MakerBot®	MakerBot Replicator Z18 3D Printer
Industrial & Scientific	Lab & Scientific Products	Multisorb Technologies	TranSorb Humidity Absorber
Industrial & Scientific	Occupational Health & Safety Products	TCP Lighting	Exit Signs
Industrial & Scientific	Occupational Health & Safety Products	UltraTech	Ultra-Microbe Boom
Industrial & Scientific	Professional Medical Supplies	Welch Allyn	Diagnostic Otoscope
Musical Instruments	Electronic Music, DJ & Karaoke	Avid Technology	Pro Tools® — Sync HD
Musical Instruments	Electronic Music, DJ & Karaoke	Native Instruments	NI brand TRAKTOR
Office Product	Office & School Supplies	Avery Products	Addressing Labels
Office Product	Printer Ink & Toner	Epson America Inc.	T0971
Office Product	Accessories	ES Robbins	Mats/Matting
Office Product	Accessories	FireKing Security Group	Media Vault
Office Product	Office & School Supplies	Humanscale	Humanscale Keyboard Systems
Software	Video editing	Corel Corporation	Pinnacle Studio
Software	Antivirus & Security	Symantec	Norton Core
Sports & Outdoors	Electronics & Gadgets	Aqua Lung	i750TC
Sports & Outdoors	Golf Balls	Callaway Golf	Warbird 2.0
Sports & Outdoors	Accessories	CamelBak	Performance Bottle
Sports & Outdoors	Accessories	Everlast Climbing	Traverse Wall® Challenge Course
Sports & Outdoors	Accessories	Hobie	MirageDrive
Sports & Outdoors	Accessories	ISM Seat	Adamo Racing
Sports & Outdoors	Accessories	JumpSport	JumpSport PowerBounce Trampoline (with enclosure)
Sports & Outdoors	Accessories	Move Collective LLC	bobble
Tools & Home Improvement	Lighting	Colonial Tin Works Inc	Solar Lid Lights® 360318
Tools & Home Improvement	Power & Hand Tools	DeckWise	STANDARD Ipe Clip
Tools & Home Improvement	Lighting	Golight Inc.	GXL
Tools & Home Improvement	Accessories & Supplies	Gorilla Ladders	Slim-Fold Work Platform, GLWP-55A
Tools & Home Improvement	Accessories & Supplies	Legrand, North America	Wall Plates
Tools & Home Improvement	Power & Hand Tools	Max USA Corp	Rebar tying tool RB398
Tools & Home Improvement	Lighting	Nanoleaf	Nanoleaf One
Tools & Home Improvement	Power & Hand Tools	Rexair LLC	Rainbow Vacuum System
Tools & Home Improvement	Power & Hand Tools	Ridge Tool Company	V2 Press Ring Actuator
Tools & Home Improvement	Generators & Portable Power	SunPower Corporation	SunPower® Flexible Solar Panel
Video Games	Xbox One	Activision	Skylanders® Trap Team Triple Trap

Notes: This table documents the representative product(s) from each firm sorted by Amazon product catalog “Department” and subcatalog “Sub-department”. The full list of products used in our sample is available upon request.

Table A.2: Distribution of the sources of P^A and P^L at relevant periods, in percent

<i>Panel A: sources of P^A</i>					
	S_0^A	S_1^A	S_2^A	S_3^A	S_4^A
The month one year before expiry	0.82	34.62	53.63	6.53	4.40
The month of expiry	0.53	26.61	62.68	7.17	3.01
The month one year after expiry	1.08	23.31	63.86	7.99	3.76
<i>Panel B: sources of P^L</i>					
	S_0^L	S_1^L	S_2^L	S_3^L	S_4^L
The month one year before expiry	0.94	7.79	75.57	0.08	15.62
The month of expiry	0.62	4.43	79.06	0.09	15.80
The month one year after expiry	1.03	4.38	77.21	0	17.38

Table A.3: Robustness checks on the baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.093*** (0.010)	-0.066*** (0.008)	-0.077*** (0.008)	-0.079*** (0.009)	-0.056*** (0.007)	-0.063*** (0.007)
Product age (in months)	-0.007*** (0.001)	-0.003*** (0.001)	0.000 (0.000)	-0.007*** (0.001)	-0.003*** (0.001)	0.000 (0.000)
New generation	-0.227*** (0.018)	-0.289*** (0.021)	-0.133*** (0.009)	-0.227*** (0.018)	-0.289*** (0.021)	-0.133*** (0.009)
One year lag of P_{ijt}^A			0.153*** (0.001)			0.154*** (0.001)
Product age $\times$ Category dummies	Yes	No	No	Yes	No	No
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	No	No	No
Patent FE	No	No	No	Yes	Yes	Yes
Product FE	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	No	No	Yes	No
Constant	5.523*** (0.009)	5.598*** (0.044)	4.348*** (0.017)	5.523*** (0.009)	5.600*** (0.044)	4.348*** (0.017)
No. products	825	825	748	825	825	748
No. patents	2,778	2,778	2,679	2,778	2,778	2,679
No. pairs	14,621	14,621	12,876	14,621	14,621	12,876
Observations	491,336	491,336	327,476	491,336	491,336	327,476
R-squared	0.902	0.904	0.897	0.902	0.904	0.897

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Robustness checks on product age

	(1)	(2)	(3)	(4)
Expiry	-0.126*** (0.013)	-0.098*** (0.010)	-0.105*** (0.010)	-0.104*** (0.010)
Product age (in months)	-0.001*** (0.000)			
Adjusted product age		-0.002*** (0.000)		
Product age (in months) dummies	No	No	Yes	No
Product age (in years) dummies	No	No	No	Yes
New generation	-0.303*** (0.022)	-0.230*** (0.018)	-0.203*** (0.018)	-0.206*** (0.017)
Month dummies	Yes	Yes	Yes	Yes
Control for price sources	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Constant	5.352*** (0.007)	5.512*** (0.008)	5.415*** (0.006)	5.261*** (0.020)
No. products	686	825	825	825
No. patents	2,208	2,778	2,778	2,778
No. pairs	9,398	14,621	14,621	14,621
Observations	313,205	488,137	491,336	491,336
R-squared	0.870	0.901	0.902	0.902

Notes: The dependent variable is $\log P_{ijt}^A$. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Comparison of truncated actual samples and placebo samples

Truncated actual samples				Placebo samples			
Beta	Std. Dev.	t-value	p-value	Beta	Std. Dev.	t-value	p-value
-0.102	0.01	-9.90	0.00	0.040	0.05	0.77	0.44
-0.101	0.01	-9.83	0.00	-0.042	0.02	-2.16	0.03
-0.103	0.01	-10.43	0.00	-0.058	0.02	-3.05	0.00
-0.098	0.01	-9.86	0.00	-0.019	0.04	-0.49	0.62
-0.098	0.01	-9.79	0.00	-0.044	0.03	-1.69	0.09
-0.097	0.01	-9.52	0.00	0.030	0.04	0.84	0.40
-0.100	0.01	-9.93	0.00	-0.027	0.02	-1.28	0.20
-0.102	0.01	-9.89	0.00	-0.002	0.03	-0.08	0.93
-0.095	0.01	-9.48	0.00	0.054	0.05	1.07	0.28
-0.097	0.01	-9.50	0.00	0.022	0.04	0.54	0.59
-0.097	0.01	-9.29	0.00	-0.04	0.02	-1.83	0.07
-0.101	0.01	-9.84	0.00	0.053	0.04	1.21	0.23
-0.099	0.01	-9.65	0.00	-0.005	0.03	-0.16	0.87
-0.098	0.01	-9.81	0.00	0.008	0.03	0.32	0.75
-0.103	0.01	-10.15	0.00	-0.015	0.03	-0.44	0.66
-0.099	0.01	-9.92	0.00	-0.024	0.03	-0.74	0.46
-0.098	0.01	-9.60	0.00	-0.050	0.03	-1.51	0.13
-0.101	0.01	-9.68	0.00	-0.043	0.02	-1.85	0.06
-0.099	0.01	-9.49	0.00	-0.012	0.03	-0.49	0.63
-0.098	0.01	-9.67	0.00	0.030	0.03	0.86	0.39

Continued on next page

Table A.5 – continued from previous page

Truncated actual samples				Placebo samples			
Beta	Std. Dev.	t-value	p-value	Beta	Std. Dev.	t-value	p-value
-0.101	0.01	-10.13	0.00	-0.044	0.02	-2.44	0.01
-0.098	0.01	-9.85	0.00	-0.016	0.03	-0.54	0.59
-0.098	0.01	-9.71	0.00	-0.002	0.04	-0.05	0.96
-0.100	0.01	-9.93	0.00	0.043	0.04	1.01	0.31
-0.100	0.01	-9.66	0.00	0.014	0.03	0.44	0.66
-0.101	0.01	-9.90	0.00	-0.013	0.04	-0.34	0.73
-0.098	0.01	-9.80	0.00	-0.003	0.04	-0.08	0.94
-0.098	0.01	-9.53	0.00	0.029	0.03	0.88	0.38
-0.102	0.01	-9.98	0.00	0.030	0.04	0.69	0.49
-0.102	0.01	-9.89	0.00	-0.048	0.02	-2.02	0.04
-0.103	0.01	-9.97	0.00	-0.040	0.02	-2.04	0.04
-0.100	0.01	-9.59	0.00	-0.047	0.03	-1.49	0.14
-0.097	0.01	-9.22	0.00	-0.008	0.03	-0.25	0.80
-0.100	0.01	-9.76	0.00	0.022	0.05	0.42	0.68
-0.098	0.01	-9.53	0.00	-0.011	0.02	-0.44	0.66
-0.100	0.01	-9.56	0.00	0.038	0.04	0.97	0.33
-0.100	0.01	-9.73	0.00	0.038	0.04	1.01	0.31
-0.100	0.01	-9.98	0.00	0.001	0.03	0.03	0.98
-0.100	0.01	-9.95	0.00	0.043	0.04	0.99	0.32
-0.101	0.01	-10.11	0.00	-0.021	0.03	-0.74	0.46
-0.102	0.01	-10.17	0.00	0.007	0.03	0.23	0.81
-0.099	0.01	-9.60	0.00	0.016	0.04	0.44	0.66
-0.099	0.01	-9.95	0.00	0.021	0.04	0.57	0.57
-0.099	0.01	-9.71	0.00	0.010	0.03	0.31	0.76
-0.103	0.01	-10.17	0.00	-0.008	0.04	-0.21	0.83
-0.099	0.01	-9.88	0.00	-0.032	0.02	-1.61	0.11
-0.100	0.01	-9.83	0.00	0.087	0.05	1.63	0.10
-0.100	0.01	-9.80	0.00	-0.012	0.03	-0.42	0.68
-0.099	0.01	-9.62	0.00	0.016	0.03	0.54	0.59
-0.098	0.01	-9.66	0.00	0.001	0.04	0.03	0.97
-0.101	0.01	-9.97	0.00	0.043	0.04	1.08	0.28
-0.102	0.01	-10.16	0.00	0.080	0.05	1.65	0.10
-0.102	0.01	-10.13	0.00	-0.029	0.03	-0.99	0.32
-0.101	0.01	-10.02	0.00	0.001	0.03	0.02	0.99
-0.100	0.01	-9.71	0.00	-0.018	0.03	-0.6	0.55
-0.100	0.01	-10.04	0.00	0.005	0.03	0.15	0.88
-0.101	0.01	-9.66	0.00	-0.001	0.03	-0.02	0.98
-0.098	0.01	-9.56	0.00	0.005	0.03	0.14	0.89
-0.102	0.01	-10.13	0.00	-0.049	0.02	-2.24	0.02
-0.099	0.01	-9.78	0.00	0.002	0.03	0.06	0.95
-0.101	0.01	-9.94	0.00	0.000	0.03	-0.01	0.99
-0.099	0.01	-9.72	0.00	0.041	0.04	1.01	0.31
-0.100	0.01	-9.57	0.00	0.042	0.05	0.80	0.42
-0.098	0.01	-9.45	0.00	-0.002	0.03	-0.07	0.95

Continued on next page

Table A.5 – continued from previous page

Truncated actual samples				Placebo samples			
Beta	Std. Dev.	t-value	p-value	Beta	Std. Dev.	t-value	p-value
-0.101	0.01	-10.17	0.00	0.031	0.04	0.73	0.46
-0.101	0.01	-9.94	0.00	0.008	0.03	0.23	0.82
-0.100	0.01	-9.97	0.00	-0.003	0.02	-0.14	0.89
-0.101	0.01	-9.89	0.00	-0.021	0.03	-0.73	0.47
-0.098	0.01	-9.53	0.00	0.005	0.03	0.16	0.88
-0.098	0.01	-9.45	0.00	-0.008	0.02	-0.34	0.73
-0.100	0.01	-9.99	0.00	0.032	0.04	0.87	0.38
-0.098	0.01	-9.80	0.00	0.019	0.03	0.58	0.56
-0.100	0.01	-9.95	0.00	-0.012	0.03	-0.37	0.71
-0.098	0.01	-9.69	0.00	-0.040	0.03	-1.17	0.24
-0.099	0.01	-9.76	0.00	0.054	0.05	1.18	0.24
-0.098	0.01	-9.44	0.00	0.015	0.03	0.49	0.63
-0.101	0.01	-9.97	0.00	-0.037	0.03	-1.32	0.19
-0.101	0.01	-9.92	0.00	0.018	0.04	0.46	0.65
-0.098	0.01	-9.33	0.00	-0.009	0.04	-0.21	0.83
-0.098	0.01	-9.70	0.00	-0.034	0.02	-1.63	0.10
-0.100	0.01	-9.73	0.00	0.021	0.04	0.54	0.59
-0.099	0.01	-9.83	0.00	0.013	0.04	0.31	0.76
-0.098	0.01	-9.58	0.00	0.033	0.05	0.73	0.47
-0.100	0.01	-9.96	0.00	-0.051	0.02	-3.42	0.00
-0.099	0.01	-9.44	0.00	0.040	0.04	1.03	0.31
-0.101	0.01	-9.74	0.00	-0.007	0.03	-0.21	0.83
-0.102	0.01	-9.97	0.00	-0.007	0.04	-0.20	0.84
-0.098	0.01	-9.47	0.00	-0.036	0.02	-2.02	0.04
-0.099	0.01	-9.75	0.00	-0.031	0.03	-0.94	0.35
-0.098	0.01	-9.62	0.00	-0.052	0.02	-2.56	0.01
-0.099	0.01	-9.80	0.00	-0.001	0.04	-0.02	0.98
-0.100	0.01	-9.64	0.00	-0.051	0.02	-2.90	0.00
-0.100	0.01	-9.58	0.00	0.033	0.03	0.95	0.34
-0.099	0.01	-9.62	0.00	-0.010	0.03	-0.34	0.73
-0.099	0.01	-9.93	0.00	-0.036	0.02	-1.90	0.06
-0.101	0.01	-9.77	0.00	-0.069	0.02	-3.38	0.00
-0.102	0.01	-10.17	0.00	-0.027	0.03	-0.91	0.36
-0.100	0.01	-9.83	0.00	0.031	0.04	0.69	0.49
-0.101	0.01	-9.93	0.00	0.008	0.03	0.24	0.81
-0.101	0.01	-9.84	0.00	0.037	0.03	1.12	0.26

Note: Standard errors clustered at the patent level. Data points differ from those depicted in Figure 9 due to a different run of the data.