Patents and Supra-competitive Prices: Evidence from Consumer Products *

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Abstract

The patent system is a central tool in innovation policy. The prospect of monopolistic pricing conferred by patent protection 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 a broad range of consumer products to the patents that protect them, we study the impact of patent protection on product prices. The empirical strategy exploits exogenous variations in patent status, namely the fall of the patent in the public domain after the statutory 20-year term limit is reached. We find that a loss of patent protection leads to a 8–10 percent drop in product prices. The price drop, which starts about one year before patent expiry, 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, K29

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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, the social planner incentivizes 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)—we call this the 'monopoly pricing hypothesis.'

The theoretical literature assumes that monopoly over an invention translates into ability to charge supra-competitive prices in the product market. However, it is not clear that this is the case. For instance, competitors could invent around the original patented invention and offer a product that looks very similar to the end consumer, thereby breaking down market exclusivity. Moreover, recurring discussions about the poor 'quality' 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 collapses.

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, the active ingredient patent *is* the drug—the patent and the product are, therefore, virtually the same. Next, the costs of drug innovation are very high whereas the costs of imitation are comparatively low, making the industry prone to free-rider problems and patent protection all the more relevant. These arguments help explain why 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). But 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.

This paper examines empirically 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 are able to 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 type and importance. It also portrays the price evolution around the time when patent terms expire. Finally, it considers how prices react to the intensity of the competition in the product market.

We find that patent expiry is associated with a 8–10 percent drop in product prices, and that the effect is larger for more important patents (i.e., patents protecting more products). We observe that the price starts dropping about one year *before* patent expiry, possibly suggesting strategic entry deterrence from the incumbent (Milgrom and Roberts, 1982; Goolsbee and Syverson, 2008). 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 the competitive pressure. Finally, placebo tests on samples of fake patent expiry events confirm the validity of our identification strategy.

The paper adds to the 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 supporting the monopoly pricing hypothesis—incumbents 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). 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 and Section 4 explains the construction of the dataset and introduces the main variables. Section 5 reports our findings. 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. Knowledge is notoriously difficult to appropriate, which translates into a wide gap between the private returns to inventive activities and the social returns. As a result, competitive markets underincentivize 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 the 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, monopoly over an invention, even if a patent is 'solid', does not translate necessarily into monopoly over the final product. The next section explains this latter point in greater detail using 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 (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,

[1] Note 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 'product' 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.

creating *de facto* a market oligopoly.[2] Computer mice at the time sold between \$200–\$400, equivalent to \$500–\$1000 in 2020 price.[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 segmenting 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

[2]Sadly 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.dougengelbart.org, last accessed on November 17, 2020.

[3]Source: https://www.macworld.com, last accessed on November 17, 2020.

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 a commercial flop. As far as we can ascertain, the effect of patents on product prices has not been tested empirically, to the notable exception of pharmaceuticals. The next section reviews the 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 pre-clinical stage to launch is estimated at about 8 percent (Paul et al., 2010). Furthermore, patents are an efficient way to deter entry in this industry. Drugs are so-called 'discrete' products with a well identified 'invention' (i.e., an active ingredient) clearly described in the patent specification. However, production is relatively cheap, and patent-protected drugs are usually sold with a high markup (Morton and Kyle, 2011). This setup is particularly attractive for generic manufacturers, who enter the market as soon as drugs lose patent protection.

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 U.S. market (Frank and Salkever, 1997) and the European market (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

In an ideal experiment, one would observe time series of the price of products, each protected by exactly one patent. We would then let some patents lapse randomly. Products with a lapsed patent would form the treatment group, and products with an active patent throughout the study period would form the control group. Every control product would be assigned a fake treatment date of a hypothetical lapse. The average treatment effect would then be the difference in the change in price around the time of patent lapse (or hypothetical lapse) between the treatment and the control group. Needless to say, such an experiment cannot be implemented in practice—patent owners are reluctant to allow scholars to let lapse randomly commercially valuable patents.

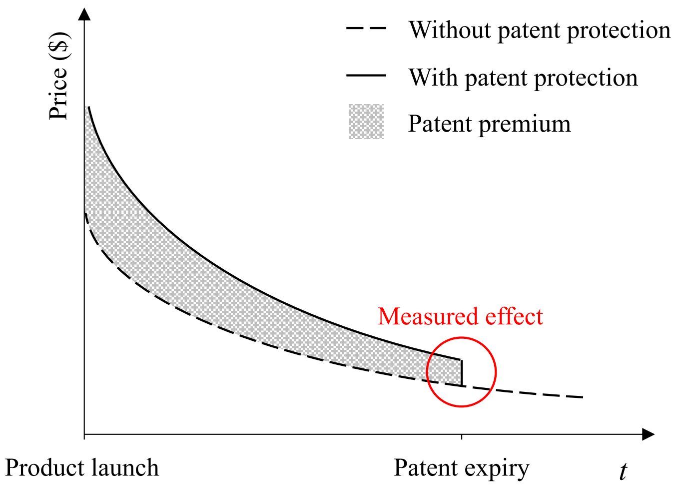
The present study exploits observational data on the price of patent-protected products that lose patent protection. There are three ways in which a product can lose patent protection. First, patents can be challenged in court and be invalidated. Galasso and Schankerman (2015) exploit data on invalidations 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 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 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

[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. It is the overall surplus that the firm can extract throughout the life of the patent (the shapes of the price slopes and the gray area are arbitrary and only serve to illustrate the point).

control for 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



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:

$$\log P_{ijt} = \beta_0 + \beta_1 Expired_{jt} + \beta_2 ProdAge_{it} + \beta_3 NewGeneration_{it} + \boldsymbol{X\gamma} + \mu_{ij} + \epsilon_{ijt} \quad (1)$$

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 β_1 captures the change in product price associated with patent expiry.

One empirical challenge lies in the fact that the price of a given product will tend to

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

naturally decline over time. 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 $\log ProdAge_{it}$). 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 with placebo 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 vector $\boldsymbol{X}$ includes a set of 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 control for 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 (μ_i and μ_j, respectively).

Finally, ϵ_{ijt} is the error term. Since the treatment is patent expiration, we estimate standard errors clustered at the patent level to account for potential serial correlations

[6] A 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.

of prices within each unit. We have also estimated the regression models with standard errors clustered at the product level, with no change to the statistical significance of the main findings.

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 for 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 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.[7] Having noted this, 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, the expiry of licensed patents merely generates 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 in a broad sense in that they are all 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.[8] 'Electronics' is the most populated category, covering nearly 40 percent of products and 50 percent of patents. Appendix Table A.1 presents a list of representative products sold by each firm.

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

[7] However, 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.

[8] Since we observe both who is the original patent assignee listed in the patent document and who claims the patent in 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 2 shows the number of patents per product, which can be seen as a measure of the 'complexity' of products.[9] 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.

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.[10] We then collected various information about products in our sample.

[9] The 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.

[10] The Amazon Standard Identification Number (ASIN) is a 10-character alphanumeric unique identifier used for product identification within the Amazon organization.

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.[11] *Keepa* tracks Amazon's products several times per day and records their prices and the inventory status (in-stock and out-of-stock).

In general terms, online retail prices are affected by the structure of the distribution channels connecting producers to consumers. Distributors, retailers, and platforms all take a 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). The Amazon platform is a competitive environment in which several sellers compete for the same product. 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 and the List price. 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.[12] The Amazon price corresponds to the market price and, therefore, forms our baseline measure of price. However, we also report estimates performed using the List price for the sake of robustness. The use of two price series provides a useful sensitivity test.

In order to have a balanced panel, we impute missing price data for both the Amazon price and the list price indices.[13] For both indices, we first reconstruct the daily price series, which we then average by month. We follow some simple rules to impute missing 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 missing data with the last known Amazon price. If there is a gap in the Amazon price series while the product

[11] See `http://www.keepa.com`, last accessed on November 17, 2020. This service has already been used in academic research, see, e.g., Reimers and Waldfogel (2020).

[12] On average, the Amazon price is 9.6 percent lower than the List price.

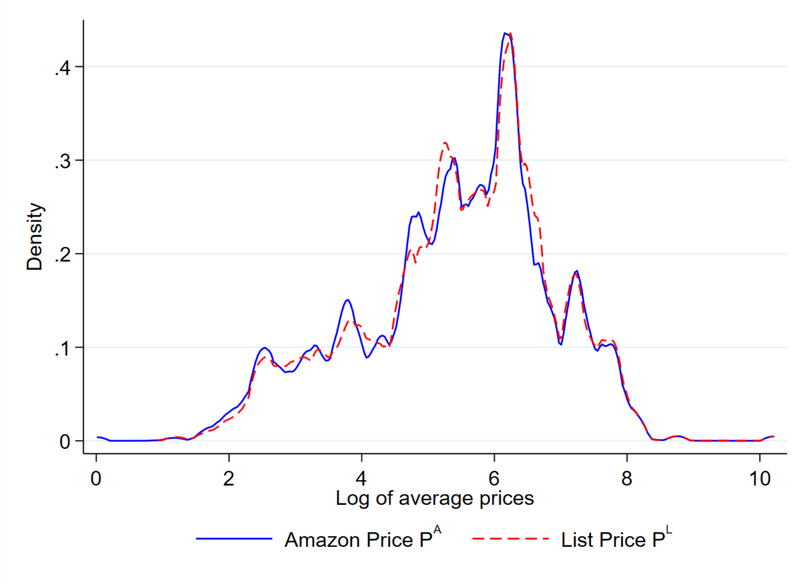
[13] *Keepa* records the prices for an item whenever a change occurs. Therefore, missing data on prices means either that the price has remained stable (such that no price was recorded) or that the item was temporarily out-of-stock (such that no price could have been recorded).

is out of stock, we populate the missing data with the last known List price. If the List price is not available (out-of-stock), we again populate the missing 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.

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^A_{0-4} and S^L_{0-4}). Regarding P^A, the variable S^A_0 takes value 1 if most of the daily prices in the given month are directly available from *Keepa*, the variable S^A_1 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^A_2 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^A_3 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^A_4 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^L_{0-4} 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 P^A and P^L variables. 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



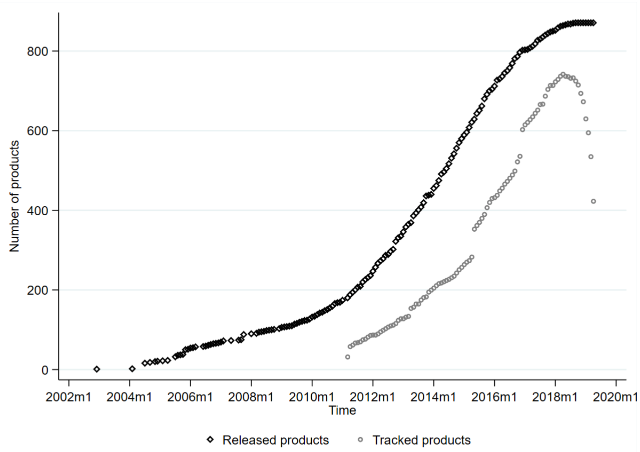
Product release date and new generation of product

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.

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

We identify substitute products 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.[14] However, the algorithm itself does

[14]For an explanation of Amazon's product recommendation method, please refer to

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.

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 0.1 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 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(imputed Amazon price)	5.42	1.55	10.22	-4.61
log(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

https://www.mageplaza.com, last accessed on November 17, 2020.

4.3 Data on patents

We collected information on patents from three sources: the USPTO Patent Maintenance Fee Events dataset (last updated on August 26th, 2019), PatentsView.org, and the Patent Claims Research dataset.[15] 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 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.

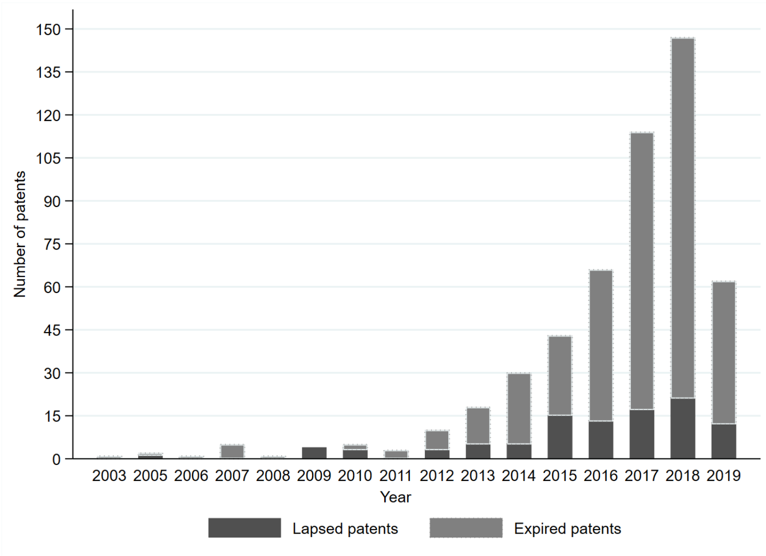
Recall that we do not exploit patents that lapse (which arise due to failure to pay the

[15] The data are available on https://www.uspto.gov, last accessed on November 17, 2020.

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.[16]

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 increases. In a robustness test, we find that excluding lapsed patents from the sample leads to similar results.[17]

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.[18] Combining the priority filing date and the product

[16]Although a patent's term can be extended under certain circumstances, for example, in case of delays in the examination. We only find 22 expired patents with an extended term. Adjusting the term or excluding the extended patents doesn't affect our results.

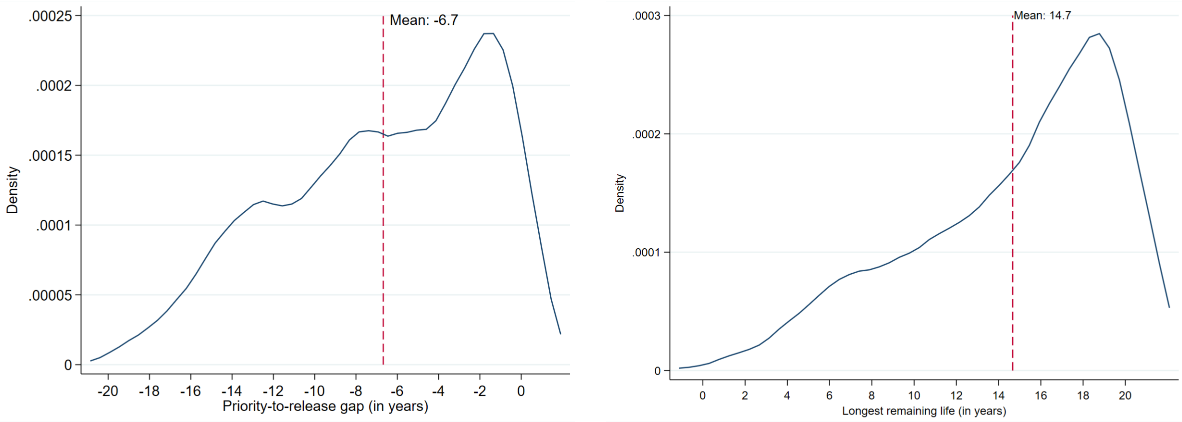
[17]Results are available upon request from the authors.

[18]According to AIA 35 U.S.C. 102(b)(1), an invention has a one-year grace period before the effective

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. As far as we can ascertain, it is the first time that such statistics have been computable.

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.

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 November 17, 2020.

Other patent-level variables

We collected additional patent-level variables in order to capture the economic value or 'quality' of patents (Lerner, 1994; Harhoff et al., 1999; Hall et al., 2005; Marco et al., 2019). We built four metrics of patent importance. The first is the number of forward citations received by the patent. The second variable is the number of distinct four digit IPC sub-classes in the patent (*IPC classes*). The third variable captures the number of independent claims in the patent (*Independent claims*). The fourth variable is the number of products protected by the patent (*Products per patent*).

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. The number of forward citations received by a patent varies from zero to 674 with an average of 56.74. The number of IPC classes for patents in our sample varies from zero to 10 with a mean of 1.33. Zeroes are associated with design rights; utility patents always have at least one IPC class. The number of independent claims varies from 1 to 26 with a mean of 3.32. On average, a patent 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 forward citations	56.74	87.36	674	0
IPC classes	1.33	1.22	10	0
Independent claims	3.32	2.53	26	1
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 the product-patent pair fixed effect, 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 the product-patent pair fixed effect. 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. The coefficient of interest drops to -0.111. Finally, column (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).

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.)

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

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.149***	-0.111***	-0.099***	-0.128***	-0.095***	-0.085***
	(0.010)	(0.011)	(0.010)	(0.008)	(0.009)	(0.008)
Product age (in months)		-0.001***	-0.002***		-0.001***	-0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
New generation		-0.241***	-0.232***		-0.241***	-0.232***
		(0.019)	(0.017)		(0.019)	(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***	5.485***	5.515***	5.382***	5.485***	5.514***
	(0.001)	(0.012)	(0.008)	(0.001)	(0.012)	(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 P^A_{ijt}. 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_{ijt}), following the same structure as in the previous table. Patent expiry results in a 7.9–9.4 percent drop in list prices (see 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***	-0.113***	-0.094***	-0.199***	-0.095***	-0.079***
	(0.017)	(0.018)	(0.018)	(0.014)	(0.015)	(0.015)
Product age (in months)		-0.005***	-0.008***		-0.005***	-0.008***
		(0.000)	(0.000)		(0.000)	(0.000)
New generation		-0.022*	-0.108***		-0.021*	-0.107***
		(0.013)	(0.009)		(0.013)	(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***	5.691***	5.877***	5.463***	5.690***	5.876***
	(0.002)	(0.009)	(0.012)	(0.002)	(0.009)	(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 P^L_{ijt}. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The 8–10 percent figure is an average obtained across a large variety of products of different prices. In the following exercise, we analyze whether the effect of expiry depends on the price of products. We break the sample into quartiles of product prices (averaged over the sample period) and report the estimates in Table 7. Patent expiry affects prices across the board, although the magnitude of the price drop varies by quartile. The drop in prices reaches a maximum of 14.9–17.2 percent in the second quartile (columns 2 and 6), which corresponds to a loss of 25-30 dollars given the average price for products in this group. For products in the highest quartile, the drop in prices upon expiry corresponds to a loss of 122–142 dollars (columns 4 and 8). Logically, the effect is the smallest in the lowest price quartile, reaching about 4 percent in columns (1) and (5).

Table 7: The effect of patent expiry on product prices by quartile of product prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expired	-0.039***	-0.172***	-0.073***	-0.101***	-0.037***	-0.149***	-0.062***	-0.086***
	(0.013)	(0.022)	(0.014)	(0.018)	(0.013)	(0.019)	(0.012)	(0.015)
Product age (in months)	-0.002***	0.005***	-0.004***	-0.006***	-0.002***	0.005***	-0.004***	-0.006***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
New generation	-0.197***	-0.536***	-0.122***	0.138***	-0.197***	-0.535***	-0.122***	0.139***
	(0.022)	(0.057)	(0.008)	(0.036)	(0.022)	(0.057)	(0.008)	(0.036)
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	3.537***	4.896***	6.169***	7.355***	3.537***	4.898***	6.169***	7.353***
	(0.011)	(0.024)	(0.013)	(0.019)	(0.011)	(0.024)	(0.013)	(0.019)
Average price ($)	39	174	405	1419	39	174	405	1419
No. products	494	104	92	135	494	104	92	135
No. patents	1,293	985	1,104	728	1,293	985	1,104	728
No. pairs	2,894	3,115	3,522	5,090	2,894	3,115	3,522	5,090
Observations	120,787	112,166	126,668	131,715	120,787	112,166	126,668	131,715
R-squared	0.934	0.339	0.435	0.865	0.934	0.339	0.434	0.864

Notes: The dependent variable is P^A_{ijt}. 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 × 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 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 columns (1) and (3), we exclude products whose launch date exceeds the one-year grace period rule. In columns (2) and (4), 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. The effect of patent expiry is similar to our baseline estimate, ranging from 8.7 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 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 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***	-0.099***	0.019	0.013
	(0.010)	(0.009)	(0.017)	(0.022)
Product age (in months)	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
New generation	-0.237***	-0.247***	-0.122***	-0.110***
	(0.018)	(0.020)	(0.033)	(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***	5.547***	4.515***	4.394***
	(0.008)	(0.013)	(0.020)	(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 P^{A}_{ijt}. 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 four 'quality' indicators in Table 4.

We implement two approaches for measuring patent importance. First, we use directly the number of products that a patent covers as an indication of the commercial value of the patent. Second, we build an index of patent importance, labeled $Importance1$, by running a principal component analysis (PCA) of the four metrics (namely, the log number of forward citations, the log number of IPC 4-digit classes, the log number of independent claims, and the log number of products per patent). We retain the component with the highest eigenvalue (greater than 1 according to the Kaiser Rule). Higham et al. (2020) argue that patent quality indicators differ by technology class. Accordingly, we also run a PCA on the four variables for each main IPC class (variable $Importance2$).

Table 9 reports the results. The expiry of more important patents, captured by the number of products that patents protect, exacerbates the decline in prices, see columns (1) and (4). However, we find no effect for traditional patent quality metrics, as captured by the composite indicators.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Expired	-0.053**	-0.098***	-0.106***	-0.054***	-0.085***	-0.090***
	(0.021)	(0.012)	(0.010)	(0.020)	(0.010)	(0.008)
Expired × log(Products per patent)	-0.016***			-0.010**		
	(0.005)			(0.005)		
Expired × $Importance1$		-0.009			-0.005	
		(0.007)			(0.006)	
Expired × $Importance2$			0.007			0.006
			(0.006)			(0.004)
Product age (in months)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
New generation	-0.236***	-0.236***	-0.236***	-0.236***	-0.236***	-0.236***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(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	5.572***	5.572***	5.571***	5.572***	5.571***	5.571***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
No. products	745	745	745	745	745	745
No. patents	2,417	2,417	2,417	2,417	2,417	2,417
No. pairs	14,055	14,055	14,055	14,055	14,055	14,055
Observations	466,331	466,331	466,331	466,331	466,331	466,331
R-squared	0.894	0.894	0.894	0.894	0.894	0.894

Notes: The dependent variable is P^A_{ijt}. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Product-level estimates

Up to this point, we have exploited the many-to-many relationship between patents and products by conducting the analysis at the product-patent level. The next table reports product-level estimates. 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.[19] 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 0.034–0.56 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***	-0.061**	-0.056**	-0.091***	-0.040**	-0.034*
	(0.025)	(0.027)	(0.027)	(0.016)	(0.018)	(0.018)
Product age (in months)		-0.002***	-0.002***		-0.001***	-0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
New generation		-0.173***	-0.180***		-0.167***	-0.180***
		(0.042)	(0.041)		(0.040)	(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***	4.583***	4.626***	4.042***	4.132***	4.175***
	(0.004)	(0.018)	(0.029)	(0.003)	(0.014)	(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 P^A_{ijt}. Standard errors clustered at the product level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

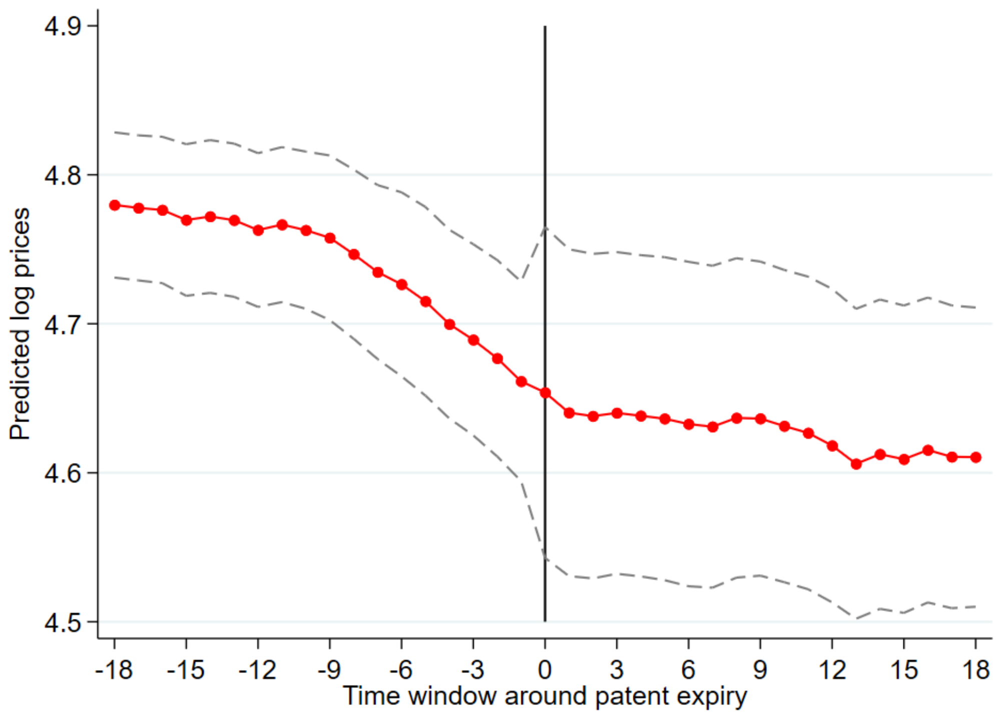
Temporal effect

In this section, we explore the temporal dimension of the decline in price with a view to shed light on its 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 (corresponding to column 3 of Table 5). We then recover

[19] The mean of $Expiry_{it}$ is 0.14 and the standard deviation is 0.34.

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. It then seems to stabilize shortly after patent expiry. 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; Morton, 2000; Goolsbee and Syverson, 2008). In this scenario, the incumbent proactively reduces the price to lower market attractiveness for would-be competitors. Alternatively, competitors might enter the market shortly before patent expiry, betting that the incumbent will not start a costly and lengthy infringement case. 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 competitive pressure.

5.2.1 An index of competitive pressure

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. We do so in two ways: with the number of similar products sold by competitors ($Substitutes$) and with the number of competing firms selling the substitutes ($Competitors$).

To examine how market competitiveness moderates the effect of patent expiry, we interact patent expiry 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. However, the squared terms are positive and statistically significant, suggesting a U-shaped relationship.

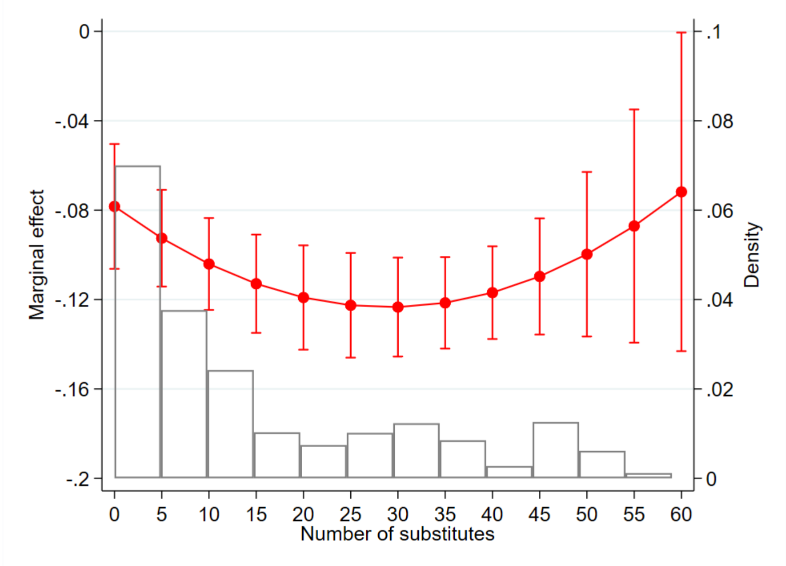
Figure 7 depicts the non-monotonic effect of competition on price using the models in columns (2) and (4). It also reports the distribution of substitute products and competitors in the sample. The existence of a U-shaped relationship makes intuitive sense. In markets with no-to-limited competitive pressure, the effect of patent protection must be limited. As competitive pressure increases, patent protection surely becomes more valuable to the firm. However, as competition further increases, competitors may have developed substitute technologies or may have invented around the patent to render the patent protection essentially useless. However, we note that most observations fall in the downward-sloping part of the effect, meaning that competition usually exacerbates the pressure on prices. In our sample, the peak is reached at about 30 substitute products and ten competitors.

Table 11: Patent expiry and competition

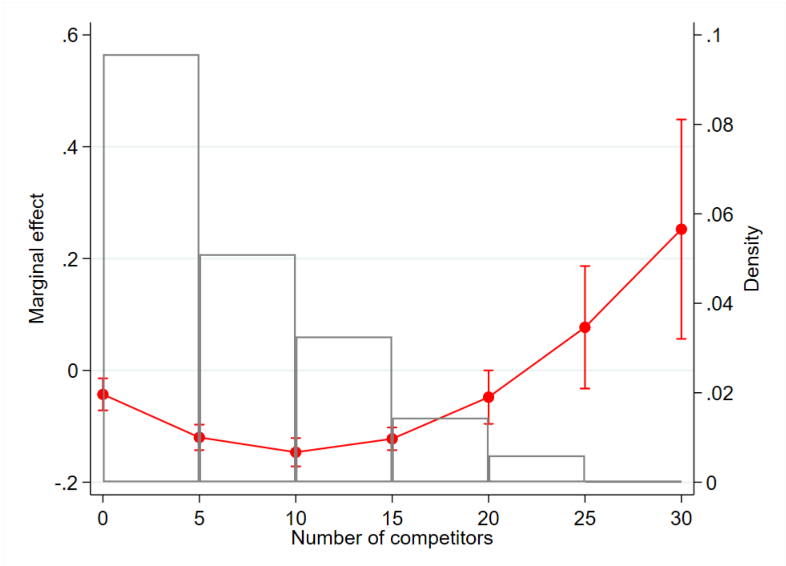
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expired	-0.090***	-0.078***	-0.081***	-0.043***	-0.082***	-0.078***	-0.079***	-0.069***
	(0.012)	(0.014)	(0.012)	(0.015)	(0.008)	(0.009)	(0.008)	(0.008)
Expired × Substitutes	-0.001*	-0.003**			-0.000*	-0.001***		
	(0.000)	(0.001)			(0.000)	(0.000)		
Expired × Substitutes^2		0.000*				0.000**		
		(0.000)				(0.000)		
Expired × Competitors			-0.003***	-0.020***			-0.001***	-0.006***
			(0.001)	(0.004)			(0.000)	(0.001)
Expired × Competitors^2				0.001***				0.000***
				(0.000)				(0.000)
Product age (in months)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
New generation	-0.231***	-0.231***	-0.231***	-0.230***	-0.232***	-0.231***	-0.231***	-0.231***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(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***	5.515***	5.514***	5.514***	5.514***	5.514***	5.514***	5.514***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(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 P^A_{ijt}. 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 two indirect evidence that the price drop following patent expiry is more pronounced in more competitive environments.

We start by estimating the impact of product quality (as assessed by customer review scores) on the price drop. To the extent that higher-quality products are less easily substitutable than lower-quality ones, we expect a lower price decrease for better 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 review scores, 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. The results suggest that a one-unit increase in the Amazon customer review score mitigates the drop in prices by about 3.0–6.5 percent. In other words, product quality eases the competitive pressure, at least in the short term.

Table 12: Patent expiry and Amazon review score

	(1)	(2)	(3)	(4)
Expired	-0.068***	-0.347***	-0.062***	-0.191***
	(0.011)	(0.083)	(0.010)	(0.040)
Expired × Amazon review score		0.065***		0.030***
		(0.018)		(0.008)
Product age (in months)	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
New generation	-0.264***	-0.263***	-0.264***	-0.263***
	(0.020)	(0.020)	(0.020)	(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***	4.991***	4.990***	4.991***
	(0.011)	(0.011)	(0.011)	(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 P^A_{ijt}. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Second, as already alluded to, the importance of patent protection varies across sectors (Cohen et al., 2000; Hall and Ziedonis, 2001; Von Graevenitz et al., 2013). It is of paramount importance in some sectors (e.g., drugs), but it plays a negligible role in others.

The multi-sector nature of products in our sample allows us to investigate whether the effect of patent expiry varies with the strength of the IP regime. We rely on the prevalence of the market for technology to quantify the role of IP in a given sector. A vibrant market for technology indicates that IP is central to technology commercialization, and sectors with such a market naturally pay more attention to IP.

For each patent, 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, it means 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.[20] 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, which we classify as strong IP regimes.

Table 13 presents estimates on the samples of strong and weak IP regimes separately. The difference between columns (1)–(2) and (3)–(4) is striking. Patent expiry in strong IP regimes leads to a 8.7–10.3 percent drop in prices, whereas it has no effect on prices in weak IP regimes. In other words, losing patent protection is particularly harmful in strong IP regimes.

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

Table 13: Patent expiry and IP regime

	(1)	(2)	(3)	(4)
	Strong IP regime		Weak IP regime	
Expired	-0.103***	-0.087***	0.008	0.007
	(0.011)	(0.009)	(0.016)	(0.015)
Product age (in months)	-0.002***	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
New generation	-0.263***	-0.263***	-0.045***	-0.045***
	(0.020)	(0.020)	(0.010)	(0.010)
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	5.582***	5.582***	5.173***	5.173***
	(0.009)	(0.009)	(0.016)	(0.016)
No. products	623	623	202	202
No. patents	1,851	1,851	927	927
No. pairs	12,606	12,606	2,015	2,015
Observations	405,385	405,385	85,951	85,951
R-squared	0.885	0.885	0.980	0.980

Notes: The dependent variable is P^A_{ijt}. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Taken together, the results presented in this section confirm the important role of competition in explaining the price decrease. The results invariably confirm that patent expiry in more competitive environments is associated with a stronger price decrease. They reinforce the conclusion that patent protection dampens competition.

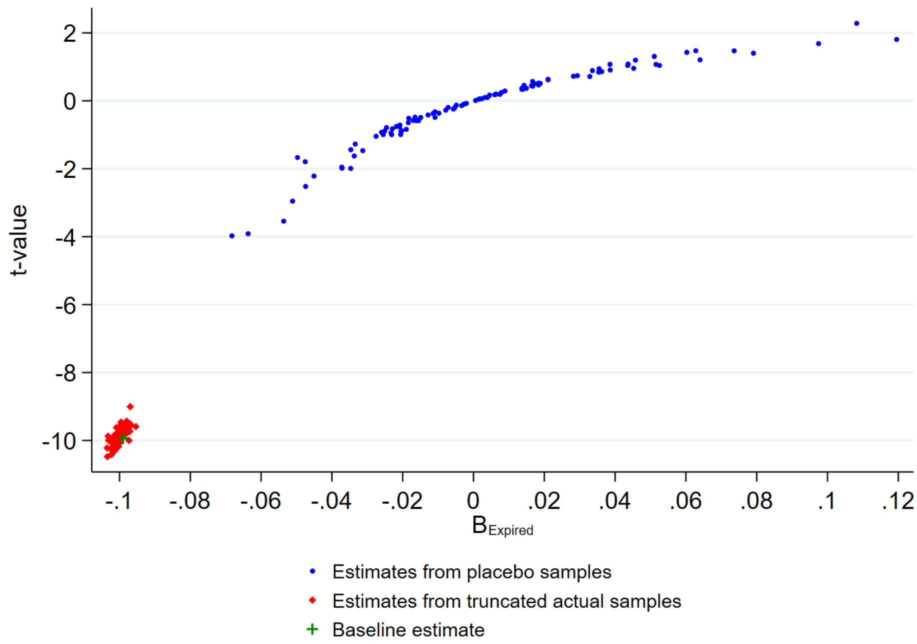
5.3 Placebo tests

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) on the real data but randomly dropping 28 percent of the observations—so the placebo and the real-but-truncated samples are of similar size. Figure 8 reports the estimated $\hat{\beta}$'s as well as their t-values. The coefficients estimated with the placebo samples are typically insignificant with roughly half of them being positive. By contrast, the $\hat{\beta}$'s estimated from the randomly reduced samples are scattered closely around the baseline $\hat{\beta}$ (-0.099).

Figure 8: Kernel density 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.

In the second placebo test, we focus only on 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 14, 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 explained by 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. Thus, if anything, controlling for product age 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. Thus, we are not concerned by the possibility that our empirical design might drive the results.

Table 14: Placebo test: the effect of patent expiry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expired	-0.094***				-0.161***			
	(0.018)				(0.014)			
Expired (2.5 years before)		0.369**				0.136		
		(0.168)				(0.109)		
Expired (3 years before)			0.380**				0.146	
			(0.153)				(0.108)	
Expired (3.5 years before)				0.118**				-0.022
				(0.053)				(0.053)
Product age (in months)	-0.002***	-0.007***	-0.006***	-0.004***				
	(0.001)	(0.002)	(0.001)	(0.001)				
New generation	-0.080***	-0.477***	-0.552**	-0.267*	-0.109***	-0.499***	-0.551**	-0.267**
	(0.012)	(0.179)	(0.210)	(0.135)	(0.008)	(0.183)	(0.209)	(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***	4.431***	4.336***	4.170***	4.661***	4.119***	4.015***	3.972***
	(0.021)	(0.085)	(0.078)	(0.045)	(0.021)	(0.051)	(0.055)	(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 P^A_{ijt}. 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. 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 (and mixed) 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. The price decline following expiry is also greater in more competitive environments, which provides further 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. 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 monopoly 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 in order to 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, but we hope that the present paper 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-2528PAI
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	Oki Data 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

Panel A: sources of P^A					
	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
Panel B: sources of P^L					
	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***	-0.066***	-0.077***	-0.079***	-0.056***	-0.063***
	(0.010)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)
Product age (in months)	-0.007***	-0.003***	0.000	-0.007***	-0.003***	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
New generation	-0.227***	-0.289***	-0.133***	-0.227***	-0.289***	-0.133***
	(0.018)	(0.021)	(0.009)	(0.018)	(0.021)	(0.009)
One year lag of P_{ijt}^A			0.153***			0.154***
			(0.001)			(0.001)
Product age * 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***	5.598***	4.348***	5.523***	5.600***	4.348***
	(0.009)	(0.044)	(0.017)	(0.009)	(0.044)	(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 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 adjusted product age

	(1)	(2)	(3)	(4)
Expiry	-0.126***	-0.098***	-0.108***	-0.087***
	(0.013)	(0.010)	(0.011)	(0.008)
Product age (in months)	-0.001***		-0.001***	
	(0.000)		(0.000)	
Adjusted product age		-0.002***		-0.002***
		(0.000)		(0.000)
New generation	-0.303***	-0.230***	-0.302***	-0.234***
	(0.022)	(0.018)	(0.022)	(0.017)
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	5.352***	5.512***	5.351***	5.504***
	(0.007)	(0.008)	(0.007)	(0.007)
No. products	686	825	686	825
No. patents	2,208	2,778	2,208	2,778
No. pairs	9,398	14,621	9,398	14,621
Observations	313,205	488,137	313,205	488,137
R-squared	0.870	0.901	0.870	0.901

Notes: The dependent variable is P^A_{ijt}. Standard errors clustered at the patent level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.