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Counterfeiting in digital technologies: An empirical analysis of the economic performance and innovative activities of affected companies

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ABSTRACT

This study analyses empirically the effects of counterfeiting on the economic and innovation performance of firms, exploiting a novel and unique dataset that integrates information on custom seizures worldwide during years 2011–2013 with financial accounting data, patent and trademark data for a sample of digital technology companies. We apply diff-in-diff models using a large control sample of non-affected firms. Results provide robust evidence that counterfeiting is associated to a negative impact on operative margins of affected companies, relative to the control sample. The analysis does not find conclusive evidence on the effects of counterfeiting on the innovation activities of affected companies. We find no evidence in support of the hypothesis that counterfeiting could also exert an indirect positive effect on the sales of genuine goods.

1. Introduction

Counterfeits are illegal products that are produced and commercialized in violation of a trademark, copyright, patent or other intellectual property rights (IPRs) (Qian, 2014b). Trade in counterfeit goods can cause damages to companies, slow economic growth and alter global competition (Grossman and Shapiro, 1988a, 1988b; Staake et al., 2009; Li and Yi, 2017; Bosworth, 2006). It also poses potential threats to the safety of citizens, in the form of goods that elude safety controls and regulations, and aliment criminal activities (Staake et al., 2009; Li and Yi, 2017; Bosworth, 2006; Peitz and Waelbroeck, 2006).

Mapping the amount and dynamics of counterfeits in the economy is a complex task for methodological purposes, but the available evidence appears consistent in pointing at a sizable and growing trend in the trade of counterfeited goods worldwide (Choate, 2005; OECD-EUIPO, 2015). According to the latest and most comprehensive estimate, counterfeits amount to approximately 2.5% of worldwide international trade and this percentage is double (5%) in the European Union (OECD, 2009; OECD-EUIPO, 2015) .[1] Recent reports further show that counterfeiting is expanding beyond the traditionally targeted sectors such as cigarettes, watches, and apparel, increasingly occurring for high-tech products, such as memory sticks, solid state drives, sound apparatus, video games (OECD, 2017) and related products (BSA, 2016). Indeed, in 2013, the global trade of counterfeited goods in the ICT sectors was estimated to be worth USD 143 bn, equivalent to 6.5% of worldwide trade in the sector (OECD, 2017).

The implications of counterfeiting for the performance of companies, particularly those that rely more on innovation, are highly debatable and difficult to estimate empirically. Economic theory has highlighted the potential damages that counterfeits can cause to economic welfare (Grossman and Shapiro, 1988a; 1988b) and evidenced that

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[1] The OECD study is based on G-TRIC indexes that estimate the relative propensity to import counterfeit products, based on the relative incidence of counterfeits among the trade partners and among the traded product categories (OECD-EUIPO, 2016). Alternative methods to estimate the aggregate volumes of counterfeiting include surveys of supply and demand (e.g., Rob and Waldfogel, 2006), economic multipliers (e.g., Siwek, 2007 for the U.S. economy), and statistical modeling (e.g., Oberholzer-Gee and Strumpf, 2009). For a comprehensive discussion of the alternative approaches and technical issues of aggregate estimates of counterfeits, see the related report of the European Commission (2012).

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strong IPRs are especially important for companies operating in highly innovative markets (Hu and Png, 2013; Branstetter et al., 2011). The reasons are multiple. Competition in industries with a strong innovative potential relies more directly on IP-based products, making these businesses more exposed to suffering direct losses from imitation (Nordhaus, 1969; Gallini, 2002). Furthermore, in the long term, the fear of imitation could discourage companies from investing in the development of new technology and from establishing potentially advantageous partnerships for the production of tech-based goods, ultimately undermining competitiveness and growth (Hu and Png, 2013; Branstetter et al., 2011) and reducing brand equity (Gabrielli et al., 2012). At the same time, the theoretical literature has also highlighted the existence of potentially positive externalities. Counterfeits -it is argued- also induce an increase in the brand circulation or user base of the products of a targeted company (Qian, 2008, 2014b), and this may benefit the company, particularly in the presence of network externalities or bandwagon effects (Conner and Rumelt, 1991; Takeyama, 1994). In these cases, a positive externality can counterbalance the negative effect of imitation partially or completely, making the net effect of counterfeiting a question that should be ultimately investigated empirically. Furthermore, prior studies have reported evidence of positive effects of imitation when taking the broad perspective of innovation generation over longer time periods. The Japanese innovation system, for example, relied significantly on reverse engineering in the 1950s and 1960s, which enabled technological catch up. This later enabled Japanese companies to conduct subsequent original development of technologies that expanded the knowledge frontier to the benefit of the broader industry (Freeman, 1987). A similar path was followed by South Korea (Hobday et al., 2004). It is an open point of discussion whether Chinese companies are following the same path. Similar to South Korea, they have entered tech-based markets predominantly by producing or distributing locally tech-based products, thanks to low-cost resources and imitation (Breznitz and Murphee, 2012) and they are now struggling to position themselves as significant legitimate producers of technologies (Minagawa et al., 2007).

The empirical evidence concerning the implications of counterfeits at present is scant, limited in scope and breadth, and inconclusive in its results (Feinberg and Rousslang, 1990; Staake et al., 2009; Qian, 2008, 2014a; Candelin-Palmqvist et al., 2012; Qian et al., 2015). Indeed, the lack of data that descends from the illegal nature of counterfeiting has impeded accomplishing large-scale, longitudinal and multi-industry analyses. The few empirical investigations that exist have attempted to investigate the implications of counterfeits only at the aggregate industry or economy level and not at the level of single companies, due to the lack of micro-level data on counterfeits.

This paper is aimed at addressing this gap. It builds an original firm-level and longitudinal dataset of digital technology companies affected by counterfeiting and on comparable digital technology companies not-affected by counterfeiting. Digital technology companies are defined as companies that produce and/or commercialize at least one physical product that incorporates a digital technology, excluding the merchandising related to the company brands. The database integrates different sets of firm-level information: on the international trade of counterfeit goods from the OECD-EUIPO (2016) database, on financial accounting data from Orbis-Bureau van Dijk (combined with Datastream), on patent data from Clarivate-Thomson Reuters, and on trademarks from the WIPO. The data are longitudinal (annual). Economic and IPRs activities of companies are observed in the years 2009–2015 and counterfeiting activities are observed annually in the years 2011–2013. The database enables unprecedented empirical analyses on the counterfeiting and on the performance of companies affected by counterfeiting. The empirical strategy relies on the use of a large control sample and difference-in-difference modeling technique. This approach is meant to cope with the inherently difficulties in estimating the effects of an only partially observable illegal phenomenon, absent a clear exogenous shock. The results indicate that digital technology companies affected by counterfeiting experience a worse dynamic of operating profits with respect to non-affected companies. We do not find evidence of positive effects of counterfeiting on sales of targeted firms. Concerning the innovation activities, the average effect on targeted companies is not statistically significant at a level sufficient to draw conclusive interpretations. None of the results is consistent with the hypotheses of net positive externalities deriving from counterfeiting as posed in the theoretical literature.

The paper is organized as follows. In Section 2, we provide a review of the empirical and theoretical studies that have investigated the phenomenon of counterfeiting, and we derive a set of research hypotheses. In Section 3, we illustrate the characteristics of the dataset and the methods adopted for the collection and integration of data. In the same section, we also provide summary statistics on the extent of the global counterfeiting activity affecting digital technology companies. In Section 4, we report the empirical analyses that aim at estimating the effects of counterfeiting on economic and innovation performance. In Section 5, we summarize and discuss the main findings.

2. Research background and hypotheses: counterfeiting and firm performance

The literature has highlighted several multifaceted consequences of counterfeiting for the market of genuine goods with implications for companies, consumers and the economic welfare (Staake et al., 2009; WIPO, 2010). The seminal theoretical works by Grossman and Shapiro (1988a and 1988b) studied the demand-price curves in markets with both counterfeit and authentic products and provided the starting point for the discussion on the effects of the counterfeit trade. The authors describe counterfeiting as a phenomenon that undermines the functionality of the property right system by enabling competitors of the original producers to appropriate part of the value of a company's intangible assets and by imposing losses of value on those consumers who have unwittingly purchased copies. They also stress that counterfeiting potentially alters the behavior of infringed firms. Indeed, these firms can adjust both the price and the quality of the genuine goods in response to counterfeiting. The direction of these changes depends on a number of market factors. In markets with free entry, counterfeiting is predicted to produce a welfare reduction, whereas in markets with a fixed number of competitors, the predictions are not univocal. In fact, a general welfare reduction is not necessarily true in markets characterized by strong network externalities or bandwagon effects (Conner and Rumelt, 1991; Takeyama, 1994). In these markets, there is a potentially positive externality for producers and consumers of original products, because customers' utility is an increasing function of the user base and counterfeits broaden the user base by making available cheap (albeit illegal) copies. For example, Conner and Rumelt (1991) maintain that, although software piracy generally harms both software firms (reducing profits) and customers (increasing prices), firms and customers could gain a positive network externality when pirate software enables a more widespread adoption of a product (see also Givon et al., 1995, and Shi et al., 2016) .[2] Under these circumstances it is possible that the externality effect in the long term generates an increase in the demand, particularly in the case of luxury goods and in brand-related business ventures (Nia and Zaichkowsky, 2000; Bekir et al., 2013; Li and Yi, 2017).

The overall effect on social welfare depends upon the values of the relevant market parameters and remains an open problem to be answered by empirical investigation. Indeed, few studies have

[2] The classical example is the market of operating systems and related software, in which it is possible that pirated software availability has indirectly contributed to consolidate the use of Microsoft Windows products (Qian, 2014b)

investigated the effect of counterfeiting empirically or assessed the response of original producers to the challenge posed by counterfeited products. The paucity of data, particularly at the firm and product levels, has traditionally been an obstacle to performing large-scale empirical investigations. In addition, these analyses are complicated by the endogeneity of the counterfeiting activities with respect to firm performance; i.e., counterfeiters typically copy successful/high-performing products and profitable brands (Berger et al., 2012).

Counterfeiting can affect company activities at various levels. In this paper, we focus on *sales, operating profits*, and *innovation activities* and develop specific research questions for each of the three, in dependence to the related academic debate.

Sales. As suggested by the theoretical works discussed above, the presence of counterfeit goods could have a mixed effect on the *sales* of the genuine products. Feinberg and Rousslang (1990) examine the welfare effects of violations by foreign players of IPRs (trademark, copyright, or patent) owned by US companies. Although they do not specifically focus on counterfeit trade, they find that the profit losses are at least as great as 1% of total sales. In a series of studies, Qian (2008, 2014a, 2014b, 2016) and Qian et al. (2015) focus on the shoe market in China to investigate the relationship between original product manufacturers and the entry of counterfeiters in the case of weak government protection. The studies found that the emergence of counterfeiting increases market prices of original goods, pushed by an increase in costs and a reduction of original goods sales in response to the counterfeit sales. The effect of counterfeiting on sales can also be indirect and depend on the change in the perceived brand value and/or the overall firm reputation induced by illegal copies. The presence of fake products can generate brand dilution and customer confusion (Feinberg and Rousslang, 1990; Liebowitz, 2005), with further negative effects on the overall reputation of the original producer (Wilke and Zaichkowsky, 1999). In this respect, many studies suggest that counterfeits reduce brand equity, particularly for luxury goods (Gabrielli et al., 2012). The reason is that illicit goods are usually of lower quality, which damages the overall attractiveness or reputation of products. Furthermore, the brand equity of status goods is especially damaged because counterfeits reduce the perception of exclusivity and uniqueness of the product by increasing the availability of cheap imitations (Fournier, 1998; Li and Yi, 2017).

In light of the abovementioned contributions, we formulate hypothesis 1 as follows.

H1. *Counterfeiting activity should be associated with an erosion in the sales of the genuine product.*

Operating profit. Companies facing the threat of counterfeiters are reported to enact anti-counterfeiting strategies and practices. Such activities can generate substantial costs for the affected firms (Staake et al., 2009; Lawson et al., 2012; Li and Yi, 2017). Among the additional costs that original producers might sustain, studies have highlighted that companies invest in product differentiation (Qian, 2008 and 2014a). Product differentiation may pertain to the features or functionality of the products, which could encompass new costly technological developments (Keupp et al., 2009). They can also pertain to other non-functional attributes of the product or of the customers' purchasing experience. For example, the company may provide elaborate packaging (e.g., expensive boxes, origin certificates), or it may include RF-IDs, digital watermarking or other high-tech labeling to track products, or it may create a chain of licensed distributors in an attempt to demarcate genuine products from copies (Holliman and Memon, 2000; Deisingh, 2005; Siror et al., 2010; Li, 2013; Guin et al., 2014; Hoecht and Trott, 2014). Such activities often imply the use of expensive tracking systems, and increased costs for marketing (Lawson et al., 2012), advertising and customer awareness campaigns (Keupp et al., 2009; Hoecht and Trott, 2014).

The application of strategies in response to actual or potential counterfeiting in some sectors may generate direct costs from the adoption of mechanisms to maintain secrecy (Lawson et al., 2012) and indirect costs to build trust with employees (Keupp et al., 2009) and secure networks with commercial partners (Hoecht and Trott, 2014) .[3] Other costs in response to counterfeiting consist of implementing enforcement measures (e.g., legal expenditures, shipment inspection procedures) and defending from liability claims, in cases of health and safety hazards for consumers (Feinberg and Rousslang, 1990; Liebowitz, 2005). Furthermore, many companies undergo costs of expensive investigations to detect counterfeiting (Hoecht and Trott, 2014; Wilson and Sullivan, 2016) after facing losses in sales, or receiving quality complaints and returns from deceived customers, or when alerted by third party or affected by large incidents of trademark violation (Green and Smith, 2002; Chaudhry and Zimmerman, 2009; Reynolds, 2011). Finally, companies that have operated in markets characterized by high risk of counterfeiting might decide to abandon those locations (Minagawa et al., 2007; Hoecht and Trott, 2014), thus incurring additional costs of relocation.

The expenses incurred by producers of genuine goods in response to counterfeiting are well documented in prior qualitative literature (Feinberg and Rousslang, 1990; Staake et al., 2009; Li and Yi, 2017). Despite so, quantitative studies have so far failed to find substantive evidence. For example, Qian (2008), who examined a sample of Chinese shoemakers, finds that the entry of counterfeiters is associated with a negative but not statistically significant change of profits. To advance the state-of-art evidence and in accordance with prior literature, we advance the following hypothesis 2.

H2. *Counterfeiting activity should be associated with a reduction in the operating profits of targeted firms.*

Innovative activities. A key implication of counterfeiting concerns the incentives to innovate of affected firms. In the classical theoretical models of IPRs, imitations expropriate the innovators from their temporary monopoly gains and should therefore result in fewer incentives to innovate (Nordhaus, 1969; Gallini, 2002).

However, the few fine-grained case studies that exist have also shown that, at least in the short term, companies might respond to counterfeiting by creating a "moving target", which should be more difficult to imitate (Hoecht and Trott, 2014). One strategy in this direction is to work on the product quality in an attempt to differentiate the offer from those of the imitators (Qian, 2008; Qian et al., 2015; Feinberg and Rousslang, 1990; Liebowitz, 2005; Lawson et al., 2012) .[4] If this is the case, counterfeiting can also induce more investments in innovation, although such investments might not necessarily be welfare-enhancing (WIPO, 2010) and they may be difficult to detect. Indeed, Qian et al., 2015 show that target companies were likely to invest in easy-to-see attributes of product differentiation (e.g., brands and original certification stamps), rather than improving functional attributes of products. Furthermore, some of the innovations introduced pertain to the tracking and identification of the genuine goods. As such, they relate to the supply chain (Lu et al., 2017; de Lima et al., 2018) or the cyber supply chain (Reddy, 2014; Boyson, 2014) and would often be developed outside of the company's boundaries.

In sum, counterfeiting is expected to induce fewer direct investments in direct product innovation by the target companies. Some target companies may also respond to counterfeiting by increasing product differentiation, but these responses are usually directed toward improving easy-to-see, non-functional attributes of the product or towards indirect innovation in product tracking and supply chain systems. Such improvements might not necessarily benefit the company or the related industry. In light of the above we formulate hypothesis 3 as

[3] Especially in the past, when textbooks and journals were not so widespread, innovations were transferred through bribing expert craftsmen to work for a new employer (Weightman, 2007).

[4] Further confirmation comes from the analysis of piracy (Raustiala and Springman, 2009)

follows.

H3. *Counterfeiting activity should be associated with a decrease (or an increase) in the innovation activities of targeted firms.*

3. Datasets and methods

3.1. Construction of the firm-level database

In order to investigate the research questions outlined in the previous section, we developed an original firm-level database. Because we are interested at both the economic and innovative implications of counterfeiting, we chose to focus on *digital technology companies*, i.e. a group of companies characterized by a strong need to invest in technological innovation, and increasingly subjected to counterfeiting (OECD, 2017) .[5] In this paper, we defined as *digital technology companies* those companies producing and/or commercializing at least one physical product that incorporates a digital technology, excluding the merchandising related to the company brands. This definition includes companies that produce and/or commercialize consumer electronics (e.g., cell phones, computer equipment, and smart watches), electronic components (e.g., sensors, microchips, displays, and remote controlling), audiovisua content stored on physical digital support (e.g., producers of music, films, and digital animation movies), and complex products that incorporate physical digital components (e.g., automotive companies producing sensors for assisted driving). Excluded by the definition are companies that produce and/or commercialize only non-physical products and services (e.g., e-commerce companies) and companies whose only physical digital product is merchandizing (e.g., football clubs that commercialize a digital watch with the name of the team).

Our database integrates and combines four sets of data: counterfeiting data, economic/financial data, patent data and trademark data. To assemble these diverse sets, we combined information from multiple sources and organized the information in a relational database in which the primary key was a single and uniquely identified company. Below, we describe the steps followed to retrieve and combine each pool of data.

Counterfeiting data. We used the OECD-EUIPO database (OECD, 2017) as a source of information concerning counterfeiting. The OECD-EUIPO database contains information about the number and value of seizures registered by customs offices in 92 economies around the world (including all the EU countries, US, Japan, and Korea among others), in the years 2011, 2012, and 2013. With over one-half million seizures, it is, at present, the most comprehensive and reliable information that exists on counterfeiting activities. We accessed the OECD-EUIPO database[6] and retrieved information about the names and incorporation countries of companies affected by counterfeiting, along with the estimated value of the goods seized, the country of origin and destination of the seized goods, a short textual description of the goods seized and the category of the goods based on the Harmonized System (HS) taxonomy.[7] A first and lengthy process concerned the identification of the digital-technology companies in the database, because these belong to different industries. We used a natural language processing algorithm supported by manual expert check in order to identify keywords describing digital technologies.[8] We obtained 91 terms (words and word combinations) related to digital technologies, which we used to identify 10 HS categories that included digital technology goods in the textual description of the goods seized in the OECD-EUIPO database.[9] This produced a list of 737 company names of potentially digital companies further searched in the Orbis-Bureau van Dijk® database. In total, 657 companies of those in the initial list of 737 were matched, equivalent to 89.1%. The matching of OECD-EUIPO with Orbis-Bureau van Dijk enabled us to retrieve additional information on the companies and to perform a final manual screening of the companies for compliance to our definition of digital technology companies. The screening entailed looking at the portfolio of products made by each company, as available in websites and advertising and was particularly selective. It resulted in a list of 260 companies that complied with our definition of digital technology companies. For these companies, we accessed information concerning counterfeit activities in the period 2011–2013.

Economic and financial data. We retrieved from Orbis–Bureau van Dijk full records on the 260 companies identified above and for a control sample. Specifically, we collected economic and financial information from 2008 to 2015 (from Income Statements and from Balance Sheets), and legal entity name, country, and dimensional category. Because the incidence of missing financial information was considerable, economic and financial information was integrated by means of the database EIKON Datastream (Thomson/Reuters®). To create a control sample of digital-technology companies likely not affected by counterfeiting, we retrieved all companies listed in Orbis-Bureau van Dijk that shared the same combination of 4-digit NACE code, geographical location and dimensional category of the 260 targeted companies. Overall, the search resulted in a control sample of approximately 29,000 companies.

Patent data. We retrieved information about patent applications from Clarivate Analytics (®Thomson Reuters), which provides information on patent filings on a global scale. For the present study, only those patents filed at the EPO, the USPTO, the JPO, or through the PCT procedure were considered. Given the timeframe of the data on seizures (2011–2013), the priority year of target patents was restricted to the interval between 2009 and 2015. The retrieved patent records were consolidated at the level of INPADOC patent families to avoid the duplication of single inventions extended to multiple patent offices. Because collecting full patent information for more than 29,000 companies would have been impossible, patent information was collected only for the 260 digital companies affected by counterfeiting plus a set of matching sample companies not affected by counterfeiting. The matching procedure is described in detail in Section 4.

Trademark data. Information were retrieved from the WIPO Global Brand Database that includes applications and registrations of trademarks from 58 world authorities and nearly 40 million records. The search strategy resembles the one used for patents.[10]

[5] The digital technology companies are also ideal to be investigated because they have a global supply chain, with a considerable part of the production taking place in Asia and because they are a B2C market.

[6] The data on counterfeiting used in the analyses were accessed exclusively on the OECD premises.

[7] HS is a multipurpose international product nomenclature developed by the World Customs Organization (WCO) to classify traded products. This classification is organized into 96 chapters, or 2-digit classes, describing broad categories of goods (e.g., HS 85-Electrical machinery and equipment and parts thereof). The 96 HS chapters are further subdivided into headings (4-digit classes) and subheadings (6-digit classes), for approximately 5.000 fine-grained categories. The OECD-EUIPO database contained information at the 2-digit level.

[8] Publications of the EC digital transformation monitor written in English were used to support the research. These included i) “Uptake of digital solutions in the healthcare industry”; ii) “The disruptive nature of 3D printing”, and iii) “Autonomous cars – the future of the automotive industry” (Digital Transformation Monitor, 2017a, 2017b, and 2017c), plus publications related to robotics and to Internet of Things (European Commission, 2016a; Friess, 2016)

[9] Collectively, we tagged all HS classes from HS84 to HS92 plus the class HS37 as potentially including digital-technology companies, resulting in 73,650 seizures associated with 737 potentially digital-technology companies. The HS classes and keyword list are available upon request to the authors.

[10] Note that trademarks covering the same IP element but registered in different offices are counted separately, because trademark data do not report a

Table 1
Distribution of digital technology companies affected by counterfeiting*.

NACE code	Description	Freq.	Perc.
26	Manufacture of computer, electronic and optical products	81	31.2%
−2611	-Manufacture of electronic components	30	11.5%
−2620	-Manufacture of computers and peripheral equipment	16	6.2%
−2640	-Manufacture of consumer electronics	14	5.4%
−2630	-Manufacture of communication equipment	10	3.8%
29	Manufacture of motor vehicles, trailers and semi-trailers	20	7.7%
46	Wholesale trade, except of motor vehicles and motorcycles	18	6.9%
59	Motion picture, video and television program production, sound recording and music publishing activities	14	5.4%
27	Manufacture of electrical equipment	11	4.2%
28	Manufacture of machinery and equipment n.e.c.	9	3.5%
82	Office administrative, office support and other business support activities	9	3.5%
60	Programming and broadcasting activities	9	3.5%
62	Computer programming, consultancy and related activities	7	2.7%
47	Retail trade, except of motor vehicles and motorcycles	6	2.3%
90	Creative, arts and entertainment activities	5	1.9%
	Other	56	21.5%
	Missing	15	5.8%
	Total	**260**	**100.0%**

* 2–4 digit NACE code classes with at least 5 companies.

3.2. Descriptive statistics on companies affected by counterfeiting

In the period 2011–2013, the 260 digital technology companies affected by counterfeiting accounted for 38,767 seizures and for a total estimated value of seized goods equal to USD 786 million. Of the companies, 41% were located in North America (US and Canada), 34% resided in either the EU28 or EFTA countries, and 23% were in Asia. European digital technology companies affected by counterfeiting accounted for 17% of the total seizures, North American firms accounted for the 49%, and Asia accounted for 33% (mostly due to few very large companies located in Japan and Korea). In line with prior studies about the counterfeiting of ICT goods (OECD, 2017), the great majority of seized goods affecting digital technology companies was shipped from China (51%) and from Hong Kong, China (41%). Approximately 3% of counterfeits seized came from Singapore.

The number of seizures is unevenly distributed across the companies in the sample. Specifically, a relatively small number of companies account for a very large number of the total seizures. The top four companies accounted for 54% of total seizures; the top ten companies accounted for 80% and the top twenty companies accounted for 89%. This large disparity in concentration might reflect in part the circumstance that some companies are more heavily targeted by counterfeiters than others are. However, it also reflects in part the larger effort placed by some companies in contrasting counterfeiting activities, compared with others.

In terms of dimension, digital technology companies affected by counterfeiting in the period 2011–2013 were disproportionately representative of large or very large entities. Of the digital technology companies affected by counterfeiting for which financial data are available, 58% had operating revenues greater than 1 B USD. Approximately 21% of the firms affected by counterfeiting had operating revenues between 50 M USD and 1 B USD. This result is in part expected, bearing in mind that counterfeiters target specifically large and wealthy brands. Such brands in turn are likely to be owned by very large corporations (Berger et al., 2012).

In Table 1, we provide a breakdown of the affected companies by main NACE code. Of the digital-technology companies affected by counterfeiting in the period 2011–2013, 31% were manufacturers of computers, electronics, and optical equipment. Collectively, the counterfeit goods of these companies represent 45% of total digital technology seizures. Among these, the manufacturers of electronic components are the largest sub-class, defined by a 4-digit NACE, followed by manufacturers of computers and peripheral equipment and consumer electronics. Examples of counterfeit goods seized related to these companies include products aimed at both the business-to-business market (e.g., sensors, LCD screens, and mobile phone components), and the consumer market (e.g., computer headphones, TV decoders, GPS navigators, and videogame consoles). Automotive manufacturers are another large group, representing 7.7% of the digital technology companies and 9.1% of total digital technology seizures.

In total, the patent search resulted in 843 thousand patent families with priority year between 2009 and 2015. Of the 260 digital technology companies affected by counterfeits, 185 (71%) filed at least one patent application in the period of observation, suggesting considerable R&D intensity. The remaining 75 digital technology companies (29%) filed no patent applications (Table 2). The average digital technology company in the sample filed approximately 3243 applications in the time interval, but the distribution is very skewed. The median company has a portfolio of 48.5 patent families; considering only firms with at least one patent, the median value rises to 443. Such a difference results from the presence of several companies that own a very large number of patents. The companies with the 10 largest patent portfolios account for approximately 50% of the patent families in the examined sample, whereas the companies with the 30 largest portfolios account for 82% of total patent families. Patent holders with fewer than 1000 families

Table 2
Distribution of firms in the sample by patent portfolio size and median value in each group.

Portfolio size (number of patent families)	Number of firms	Perc. of firms	Median portfolio size
Zero	75	29%	0
From 1 to 25	42	16%	8
From 26 to 50	14	5%	39.5
From 51 to 100	11	4%	64
From 101 to 250	18	7%	170
From 251 to 500	11	4%	400
From 501 to 1000	14	5%	716
From 1001 to 2500	25	10%	1726
From 2501 to 5000	14	5%	3345.5
From 5001 to 10,000	12	5%	7762
From 10,001 to 25,000	16	6%	16,624.5
From 25,001 to 100,000	8	3%	51,820
Total	**260**	**100%**	**48.5**

(*footnote continued*)
priority or a family identifier. The reconstruction of families requires the adoption of techniques that are not automated and are out of the scope of this study (see for example: Block et al., 2014).

Table 3
Distribution of firms in the sample by trademark portfolio size and median value in each group.

Portfolio size (number of trademarks)	Number of firms	Perc. of firms	Median portfolio size
Zero	23	9%	0
From 1 to 25	47	18%	7
From 26 to 50	28	11%	35.5
From 51 to 100	23	9%	76
From 101 to 250	43	17%	154
From 251 to 500	29	11%	318
From 501 to 1000	28	11%	635.5
From 1001 to 2500	29	11%	1581
From 2501 to 5000	6	2%	3073
From 5001 to 10,000	4	2%	6709
Total	**260**	**100%**	**118**

represent 42% of the sample; 29% of the companies have filed applications for more than 1000 patent families. The largest share of patent families (84.2%) is owned by electronics companies (57.3%); automotive companies (8.8%) own approximately 13.9% of patent families, whereas media corporations (11.9%) account for only 31 patent families, corresponding to 0.3% of the total patent families.

The analysis of trademarks data resulted in 132 thousand items between 2009 and 2015. Only 23 of the 260 digital technology companies affected by counterfeits (9%) have not applied for any trademark (Table 3). The average company filed about 510 trademarks and the median company filed about 118 applications (the value is 156 when excluding those without trademarks). The companies with the 10 largest trademark portfolios account for approximately 35% of all trademarks in the sample (the top 30 portfolio holders represent 63% of the total). The largest share of trademarks (56%) is owned by electronics companies (those with at least one trademark are 57% of the sample).

4. Results

4.1. Likelihood of being targeted by counterfeiting

Prior to testing our hypotheses, we wanted to gain a deeper understanding of the firm-level characteristics affecting the likelihood of being targeted by counterfeiters. To this end, we run a set of Logit models on the dataset including both digital firms subject to counterfeiting and a control sample of firms not targeted. The dependent variable is dichotomous and takes the value one for the firms that had been affected by at least one counterfeiting case in the years 2011–2013, and zero otherwise. We included in our model as explanatory variables the company size (SIZE), computed as the logarithm of the operating revenues.[11] In addition, we included firm profitability, as measured by return on assets (ROA), i.e., the ratio of earnings before interest and taxes (EBIT) to total fixed assets; the amount of intangible assets (INTANG); and the growth rate of the business (GROWTH), measured as the growth rate of operating revenues over a two-year period before the window of observation of counterfeits. We also included sector dummy variables defined at the NACE 2-digit level and country dummies based on the company's country of incorporation.[12] To limit the incidence of potentially confounding effects, all dependent variables based on financial accounting data refer to the fiscal year 2010, i.e., prior to the window of observation of the counterfeiting event. All models include a set of country dummies, identified as the country of incorporation of the company. Table 4 reports the results on the set of Logit model estimates on the likelihood of being affected by counterfeiting.

All models indicate a positive and highly significant correlation between company size and the likelihood of being affected by counterfeits. This evidence holds both when using a continuous indicator of firm size (Models: I and II) and when adopting macro size classes (Models: III and IV). This positive correlation is also robust to the inclusion of sector and country dummies. Interestingly, a positive correlation between the firm-level endowment of intangible assets (INTANG) and the likelihood of being affected is observed in all models and it is statistically significant in models II, III and IV. This result is consistent with prior studies based on survey data (Berger et al., 2012).

The performance of the firm in year 2010, measured by the return on assets (ROA), does not have a statistically significant correlation with the likelihood of being affected by counterfeiting activity.

The growth rate of the operating revenues (GROWTH) in the two years before the interval of observation of the counterfeiting cases shows a negative correlation with the likelihood of being a target, albeit this is not always statistically significant. This negative correlation suggests that companies that were targeted by counterfeiting activities had a lower-than-average growth of operating revenues in the years before the window of observation. Such a result should be interpreted with caution. It could in fact be due to counterfeiting activities already in place in 2010. Moreover, it could also be due to the natural circumstance that larger firms, which are more frequently targeted, experience lower growth because growth rates tend to be negatively related to size.

Models II and IV adopt a single dummy variable (EU countries) that takes the value one for those companies located in any of the EU 28 countries. In this case, estimates suggest that after considering company-specific effects such as size or profitability, firms based in the EU28 have a relatively lower likelihood of being affected, compared with those located in other areas. The effect is highly significant and robust to alternative model specifications in which other firm-level covariates are excluded. Based on the available data, it is not possible to know to what extent the result of a lower incidence of counterfeiting targeting EU28 firms derives from different anti-counterfeiting policies set in place by EU28 governing authorities or by EU-based firms. Regardless of the reason, digital technology companies located in the EU28 appear to be relatively less affected by counterfeiting activities than are digital technology companies located elsewhere. This effect is present after controlling for sector and size of the firms, hence netting potential structural differences between EU- and non-EU-based firms.

4.2. Counterfeiting and economic performance: operating revenues and operating profits

Hypotheses 1 and 2 concern the correlation of counterfeiting with the operating revenues (sales) and operating profits of target companies respectively. The nature of the correlation between counterfeiting and these outcomes variables at the firm level is likely to be affected by endogeneity (selection into treatment), which might lead to the estimation of a biased positive correlation between counterfeiting and sales. This is because counterfeiters typically target high-performing products and profitable brands (Berger et al., 2012). In order to cope as much as possible with this problem, we rely on the longitudinal nature of our data and on the observation of companies that were and were not target by counterfeiting in the observation period. To this aim we employ difference-in-difference models using year 2010 and 2014 as pre- and post-treatment time references. In order to check for the applicability of the diff-in-diff analysis, we ascertained the presence of a common trend for all the outcome variables between treated and non-treated companies before the treatment period. We did so by comparing

[11] In models III and IV of Table 4, we replaced the single continuous variable SIZE with a set of dummy variables identifying the company firm class. (BIG equals one for companies with a turnover above USD 1B; LARGE equals one for companies with a turnover between USD 50 million and USD 1 bn; SME, the baseline variable, equals one for companies with a turnover equal to or less than USD 50 million).

[12] The omitted reference dummies are the sector NACE 96 ("Other personal service activities") and the US among countries.

Table 4
Logit models. Dependent variable: likelihood of being affected by counterfeits in the years 2011–2013. Covariates set at year 2010. Sample including non-counterfeit control firms. Omitted category for the size dummies: SME.

Variables	Model I	Model II	Model III	Model IV
Size	0.9071***	0.8983***		
	(0.082)	(0.074)		
Big			4.4719***	4.5434***
			(0.584)	(0.513)
Large			1.9414***	2.0826***
			(0.589)	(0.523)
Roa	0.2157	0.2469	0.1506	0.1670
	(0.269)	(0.259)	(0.229)	(0.224)
Growth	−1.0197**	−1.2221***	−0.6322	−0.7901**
	(0.500)	(0.430)	(0.432)	(0.368)
Intang	0.0296	0.0408*	0.1229***	0.1549***
	(0.022)	(0.022)	(0.032)	(0.034)
EU Countries		−1.3629***		−1.6306***
		(0.270)		(0.253)
Country dummies	YES		YES	
Sector dummies	YES	YES	YES	YES
Constant	−15.4494***	−15.7435***	−6.0843***	−6.5192***
	(1.668)	(1.557)	(1.313)	(1.249)
Observations	7183	7183	7183	7183
Chi-Sq	611.9	742.7	555.4	670.7
Log-Likelihood	−239.9	−287	−268.2	−323
Pseudo R2	0.561	0.564	0.509	0.509

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the growth rates of the outcome variables that proved to be not statistically different, supporting the viability of the method (Table 8 in the Appendix provide the corresponding statistics).

H1 is investigated in Model I of Table 5, which reports the results of the diff-in-diff estimate where the outcome variables is operating revenues. The model controls for sector and country dummies. The results for the operating revenues indicate that firms affected by counterfeits (i.e., the treated group) show on average larger values compared with the control group (firms not affected by counterfeits), while the time dummy reports a negative sign. The difference of such differences (diff-in-diff) takes a negative sign, albeit not statistically significant. This is suggestive that the superior performance (higher operating revenues) of the treated group compared with the non-treated group before the counterfeiting remained after the treatment but had shrunk. However, this difference is not statistically significant, at conventional confidence levels. Therefore, the results did not provide full support to H1 that counterfeiting is associated with a decrease in the sales of genuine goods.

The hypothesis H2 regards the operating margins of companies targeted by counterfeiting and is investigated in Models II and III of Table 5. We use two measures of operating profits: Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) and Earnings Before Interest and Taxes (EBIT). As before, all models include controls variables for sectors and countries. The treated companies have larger operating profits both before and after the treatment period. However, the difference between the two groups over time has reduced. Indeed, both models indicate a negative and statistically significant difference between the treatment (i.e., being affected by counterfeit) and the control in the growth of the EBITDA and the EBIT. The evidence suggests that the companies that were targeted by counterfeiting experienced a reduction in the operative margin that is not explained by trends, consistent to the hypothesis H2.

Table 5
Difference-in-difference models. Dependent variable: operating revenues (Model I), EBITDA (II), and EBIT (III). Treatment variable: firm targeted of counterfeit. .

Dependent variable	Model I Operating Revenues	Model II EBITDA	Model III EBIT
Treated x Time (diff-in-diff)	−89.950	−51.895**	−36.221***
	(100.908)	(21.316)	(10.345)
Treated dummy	2548.174***	533.133***	189.502***
	(224.001)	(42.584)	(17.475)
Time dummy	−19.010***	−0.688	−1.048**
	(2.797)	(0.543)	(0.286)
Sector and country dummies	Yes	Yes	Yes
Constant	337.408***	91.761***	33.311***
	(82.029)	(16.661)	(7.000)
Observations	35,585	28,327	36,007
R-squared	0.24	0.32	0.19

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

We replicated the analyses on specific subsamples of companies as robustness checks. Specifically, we limited the estimation to the companies in the "Electronics" sector[13] and to those affected by multiple counterfeit events). The results are reported in Table 8 and Table 9 of the Appendix.

The results of the diff-in-diff models and the robustness checks suggest the presence of a negative but not significant effect of counterfeiting on the volume of operating revenues. Instead, the results on operating margin, expressed in terms of either EBITDA and EBIT, suggest the presence of a robust and statistically significant negative effect of counterfeiting. Overall, they appear to indicate that companies affected by counterfeiting might not have experienced a significant reduction in sales, but they have nonetheless experienced a reduction in profits, compared with companies not affected by counterfeiting, suggestive that they have incurred additional costs not compensated by revenues in the period of observation.

4.3. Counterfeiting and innovation activity

In order to test the effect of counterfeiting on the innovation performance of digital technology companies (H3), we used three outcome variables: the book value of the intangible assets,[14] the annual number of new patent family filed, and the annual number of new trademarks applications. The retrieval of patent and trademark information for the entire sample, including more than 29,000 companies, would have required the application of complex automated procedures with expected low accuracy. We therefore opted to use a different methodological approach. We first identify a sample of comparable non-treated companies with a one-to-one matching procedure and we then searched manually for data on patents and trademarks of the matching sample. This enabled us to carefully control for company name variations and avoid instances of false positive results. The sample of paired companies was constructed by applying a Propensity Score Matching (PSM) strategy (Caliendo and Kopeinig, 2008). The selection model for the PSM was run on pre-treatment data, i.e. for the year 2010, relying on the coefficients resulting from the Logit model described in Sections 4.1 and forcing the selection of the non-treated firm in the subsample of firms operating in the same macro-sector of the focal counterfeited company. The procedure employed a one-to-one nearest-neighbor matching with replacement and a tolerance threshold for the similarity in the propensity score of 0.05 (Cochran and Rubin, 1973).

Coherently with the methodological approach described in the previous section, diff-in-diff models have been employed to test the effect of counterfeiting activities on the innovation performance of digital technology companies, controlling for sector and country specificities. The results are reported in Table 6.

Model I of Table 6 measures the innovation activities through the

[13] "Electronics" includes the following NACE codes: 26, 27, 28, 32, 46, 47, 58, 61, 62, 63.

[14] The value of R&D expenditure was not available for most of the companies; hence, it was not possible to include it in the analysis.

Table 6
Difference-in-difference models. Dependent variable: Book value of Intangible Assets (Model I), Number of Patents (II), and of Trademarks (III). Treatment variable: firm targeted of counterfeit.

Dependent variable	MODEL I Intangible Assets	MODEL II Number of Patents	MODEL III Number of Trademarks
Treated x Time (diff-in-diff)	6.230	−62.731	9.358
	(15.406)	(42.816)	(24.852)
Treated dummy	308.700***	563.550***	21.041
	(32.165)	(163.856)	(19.532)
Time dummy	0.287	10.605	−9.921
	(0.389)	(19.361)	(21.712)
Sector and country dummies	Yes	Yes	Yes
Constant	111.555***	−692.989**	20.269
	(16.541)	(328.241)	(53.811)
Observations	42,338	642	642
R-squared	0.25	0.26	0.35

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

book value of intangible assets. The results indicate that the treated group (counterfeited firms) has a larger average volume of intangible assets compared with the control group, while the time dummy does not show a significant result. The diff-in-diff interaction term is positive and not statistically significant. Model II of Table 6 report results with patents as the outcome variable. In this case, the treated companies have larger patent portfolios. The difference of difference is negative, suggestive that the difference has shrunk, but the related standard errors are very high, and the result is not statistically significant at conventional confidence levels. Concerning trademarks, we do not observe statistically significant differences.

In order to shed more light on the results, we performed an additional sample comparison of the innovation activities of the treated and control groups. Table 7 reports and compares the differences in patent and trademark filings between the counterfeited companies and the corresponding matched firms (Columns I and II) and the difference within each subsample before and after the period when counterfeiting is observed (Columns III and IV).

The analysis shows that, before the window of observation (years 2009–2010), the companies affected by counterfeiting filed a significantly higher number of both patents and trademarks than did the companies not affected by counterfeiting (Column I). The same test performed after the window of observation (Column II), i.e., in the years 2014–2015, indicates that the samples still have a significant difference in means of both patents and trademarks. Nonetheless, Column III indicates that, on average, the number of patents filed by companies targeted by counterfeiters decreased after the counterfeiting period, while the average number of patents filed by companies not targeted remained approximately the same (Column IV). Conversely, the number of trademarks remained overall unchanged over time for both targeted (Column III) and untargeted companies (Column IV). The results hint that targeted companies, over time, were filing fewer patents compared to non-targeted companies, while their investments in trademarks grew proportionately to those of non-targeted companies.

The results derived from the different models on the outcome variables that proxy innovation effort do not indicate a clear average negative effect of counterfeiting. The digital technology companies that were affected by counterfeiting on average increased their intangible assets volume and trademark filing in a proportion that kept their advantage approximately constant compared to companies not affected by counterfeiting. The companies also continued to aliment their patent portfolios during the treatment period, but by less than the digital technology companies that were not affected by counterfeiting. However, this difference is not statistically robust to the inclusion of sector dummies. Hence, we do not find robust evidence in support of our hypothesis H3 that counterfeiting might decrease the innovation activities of targeted firms.

5. Discussion and conclusions

The study presented is the first large-scale analysis of the effects of counterfeiting using company-level data. The analyses have been possible thanks to the creation of a novel and unique database developed by combining the OECD-EUIPO data on international trade of counterfeits with firm-level data on financial accounting data and patent and trademark activities. In the paper, we have investigated the firm-level correlation between counterfeiting and various indicators of economic and innovation performance, by means of difference-in-difference estimates. The analysis focused on digital technology companies that have been targeted by counterfeit during the years 2011–2013. The results indicated that counterfeiting activities were targeting specifically larger companies and having a high propensity to innovate, as proxied by larger volumes of intangible assets. Target companies also have on average larger patent and trademark portfolios prior to the observation of counterfeiting activities.

Our estimates indicate that digital technology companies targeted of counterfeiting do not experience lower sales, but they do experience lower operating profits with respect to digital-technology companies not affected by counterfeiting. The negative effect of counterfeiting on margins is registered both in terms of EBITDA and EBIT. This result could be interpreted as suggesting that counterfeiting does not provoke gross losses of sales, but this is so because the targeted companies incur into larger operating costs in order to protect and/or contrast counterfeiting. Therefore, we can conclude that counterfeiting negatively impacts the profitability of companies.

Concerning innovation performance, the study finds no strong evidence of impact, either positive or negative, of counterfeit. We find, however, moderate evidence that the targeted companies alter their propensity to patent over time. In particular, the size of the patent portfolios of targeted companies, over time, increases less than the size of patent portfolios of non-targeted companies. Instead, the size of the trademark portfolio follows a similar dynamic both for targeted and not-targeted firms. If we consider trademarks as associated to no-functional inventions, this evidence could be interpreted as indicating

Table 7
Average patent and trademark activities of companies, affected vs. not affected by counterfeiting. Between and within group differences.

	Column	I	II	III	IV
		Between groups Diff: targeted – not targeted		Within groups Diff: (2014/15) – (2009/10)	
		Before (2009/2010)	After (2014/2015)	Targeted by counterfeiting	Not targeted by counterfeiting
Patents	*Average difference*	1097.1***	849.5***	−243.1**	12.5
	(St. error)	(222.5)	(188.5)	(118.7)	(25.3)
Trademarks	*Average difference*	82.8***	87.0***	8.2	4.0
	(St. error)	(30.8)	(40.6)	(18.0)	(8.5)

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$.

that counterfeiting induces companies to invest more in non-functional innovation, compared by functional innovation. However, when we control for sector and country specificities, the standard errors are too large, and the relative variations are not statistically significant, regardless of the indicator of innovation performance used. Hence, the analysis did not find a statistically significant effect of counterfeiting on innovation performance.

In conclusion, the study shows with considerable certainty that counterfeiting is associated with a worsening of the profitability of the digital technology companies. The digital technology companies affected by counterfeiting did not appear to experience a loss of sales but had on average a worse dynamic of operating profits in comparison to the digital technology companies not affected by counterfeiting in the same years. The results of lower operating profits can be explained with some of the evidence reported by prior studies. This evidence indicated that the companies targeted by counterfeiting react by increasing expenses in product differentiation (Alacer et al., 2017) and in anti-counterfeiting practices, ranging from conspicuous packaging to certifications of origin, owned sales channels, or other procedures aimed at monitoring the circulation of counterfeits (Staake et al., 2009; Holliman and Memon, 2000; Siror et al., 2010; Li, 2013). Our results indicate that, collectively, these strategies can contribute to lower the profitability of targeted companies, as expressed by their operating profit, and are consequently harming the profitability of companies targeted by counterfeiting. Moreover, we found no evidence in support of the hypotheses advanced in economic theory (Grossman and Shapiro, 1988b; Takeyama, 1994) that counterfeiting could create positive externalities that increase the sales of affected companies.

The study has a number of methodological limitations that are worth considering. First, the study considered only a limited time window. It is possible that the reaction of companies to counterfeiting evolves over time, such that some of the effects, particularly those related to investment in innovation, would be evident only in a longer time span. Future studies should replicate the analysis with an extended time-window to capture the medium-to-long-term effects of counterfeiting. Furthermore, because the exact start and end of the counterfeiting activities are not known, it is possible that different effects are found on longer timespans. Second, the study is based on data about seizures of counterfeited goods detected at customs. Customs seizures have progressively emerged as the most comprehensive and reliable source of data on the subject (Staake et al., 2009). However, they are not exempt from limitations. Due to the illicit nature of the phenomenon, not all counterfeits can be detected and seized. Seizures represent only a share -an unknown share- of the total counterfeits that are illegally traded across the borders. They do not account for counterfeits produced within a country that do not travel across the borders or for non-physical products (e.g., piracy of software that travels online). Furthermore, customs data are not originated for statistical purposes; they are the result of controls applied by custom officers, which are not necessarily random. Indeed, customs officers are more likely to detect products that infringe trademarks, compared with copyrights and patents, because the latter are less immediately visible and demonstrable (Berger et al., 2012;). In addition, customs officers respond to the priorities of national and policy authorities (e.g., they are more focused on products that pose threats to the health of citizens or to trade linked to terrorism or criminality). Future works could complement our analysis with alternative sources of data. Third, the empirical strategy relied on diff-in-diff estimates. The identification of the effect could be improved by future analyses that exploit exogenous shocks (e.g., changes in custom seizures policies or international trade law). Fourth, this study showed a negative effect of counterfeiting on economic performance but could not estimate the magnitude of this effect, nor could it estimate whether the effect varies with the intensity of counterfeit trade. Future analyses could advance the understanding of the effects of counterfeiting by using product-level data, which can provide insights on magnitudes. Fifth, the study considered only digital technology companies. Caution is required when generalizing the findings beyond the studied industry. Prior theoretical studies have pointed at effects that could vary depending upon the related market (Qian et al., 2015). More analyses on different industries and different sets of data are needed to assess the degree to which these findings can be generalized. Finally, the analyses did not account for potential network externalities generated by the circulation of counterfeits that could have occurred in the same or in complementary industries.

Despite these limitations, the evidence provided is the study are unique because they represent the first attempt to provides a clear and rigorous assessment of the effect of counterfeiting at the company-level. The results document a loss of operating profits of digital technology companies affected by counterfeiting. Furthermore, the study rules-out with considerable certainty the presence of positive spillovers associated to counterfeiting in the sample considered.

Counterfeiting activities are a serious concern for governments and trade authorities worldwide. The recent trends have shown that counterfeiting is increasing in volume and share and that it increasingly affects goods that incorporate digital technologies (OECD, 2009; OECD-EUIPO 2017 OECD, 2017). Our results restate the importance of policy intervention to enhance the protection of markets from the illegal trade of counterfeits, not only for goods like cigarettes, apparel and watches that are a traditional target, but also for high-tech hardware. The IPRs value in these industries is known to reside in large part in patents and copyrights, which are usually less easy to detect compared to trademarks. Consequently, our results suggest that governments and public authorities should be concerned with developing more effective methods of surveillance to prevent illegal trade of digital products. Absent an effective protection, counterfeiting may seriously damage the profitability of innovative companies, which is critical for the social and economic prosperity of countries, with potentially negative consequences for productivity, employment, economic growth and government taxes.

CRediT authorship contribution statement

Vincenzo Butticè: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Federico Caviggioli:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Chiara Franzoni:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration, Supervision. **Giuseppe Scellato:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Piotr Stryszowski:** Conceptualization, Data curation, Writing - review & editing. **Nikolaus Thumm:** Conceptualization, Methodology, Data curation, Writing - review & editing, Supervision.

Declaration of Competing Interest

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2020.103959.

Appendix

Table 8, 9, 10, 11, 12

Table 8
Average growth rate of the outcome variables in the pre-treatment period and comparison between treated and non-treated firms (no significant difference was found).

Variable	Mean growth Sample: non-treated	Mean growth Sample: treated	Difference
Operating revenues	0.064	0.075	−0.011
	(0.003)	(0.015)	(0.025)
EBITDA	0.060	0.087	−0.011
	(0.005)	(0.023)	(0.034)
EBIT	0.083	0.077	0.006
	(0.005)	(0.027)	(0.042)
Intangible assets	0.001	0.053	−0.051
	(0.007)	(0.051)	(0.054)
Patents	0.451	0.360	0.091
	(0.212)	(0.154)	(0.299)
Trademarks	1.066	0.636	0.429
	(0.294)	(0.170)	(0.354)

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 9
Difference-in-difference models. Dependent variable: Operating Revenues (Model I), EBITDA (II), and EBIT (III). Treatment variable: firm targeted of counterfeit. Subsample of companies in the sector “Electronics”.

Dependent variable	Model I Operating Revenues	Model II EBITDA	Model III EBIT
Treated x Time (diff-in-diff)	−120.795	−82.914***	−49.018***
	(90.951)	(16.308)	(7.158)
Treated dummy	2839.957***	606.927***	223.092***
	(70.368)	(12.418)	(5.535)
Time dummy	−23.791**	−2.354	−2.138***
	(8.458)	(1.864)	(5.738)
Sector and country dummies	Yes	Yes	Yes
Observations	20,631	16,535	20,648
R-squared	0.27	0.32	0.21

Standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.10$.

Table 10
Difference-in-difference models. Dependent variable: Operating Revenues (Model I), EBITDA (II), and EBIT (III). Treatment variable: firm targeted of counterfeit. Subsample of companies affected by multiple cases of counterfeit in the time window.

Dependent variable	Model I Operating Revenues	Model II EBITDA	Model III EBIT
Treated x Time (diff-in-diff)	−67.718	−59.167***	−40.289***
	(79.992)	(13.565)	(6.172)
Treated dummy	2827.254***	569.955***	204.255***
	(61.191)	(10.316)	(4.716)
Time dummy	−18.910***	−0.673	−1.046**
	(6.568)	(1.354)	(0.503)
Sector and country dummies	Yes	Yes	Yes
Observations	35,538	28,284	35,963
R-squared	0.25	0.32	0.19

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 11
Difference-in-difference models. Dependent variable: Book value of Intangible Assets (Model I), Number of Patents (II), and of Trademarks (III). Treatment variable: firm targeted of counterfeit. Subsample of companies in the sector “Electronics”.

Dependent variable	Model I Intangible Assets	Model II Number of Patents	Model III Number of Trademarks
Treated x Time (diff-in-diff)	1.861	−94.942	19.863
	(12.790)	(291.450)	(32.226)
Treated dummy	336.521***	610.609***	−4.562
	(9.823)	(230.788)	(25.518)
Time dummy	−0.502	2.345	−19.527
	(1.276)	(249.081)	(27.541)
Sector and country dummies	Yes	Yes	Yes
Observations	22,478	408	408
R-squared	0.23	0.26	0.28

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 12
Difference-in-difference models. Dependent variable: Book value of Intangible Assets (Model I), Number of Patents (II), and of Trademarks (III). Treatment variable: firm targeted of counterfeit. Subsample of companies affected by multiple cases of counterfeit in the time window.

Dependent variable	Model I Intangible Assets	Model II Number of Patents	Model III Number of Trademarks
Treated x Time (diff-in-diff)	12.290	−75.615	9.324
	(10.110)	(224.810)	(26.542)
Treated dummy	339.311***	729.758***	39.713*
	(7.676)	(163.585)	(21.101)
Time dummy	0.301	10.605	−9.921
	(0.846)	(190.835)	(22.531)
Sector and country dummies	Yes	Yes	Yes
Observations	42,286	544	544
R-squared	0.25	0.30	0.40

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

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