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Impact of counterfeiting on the performance of digital technology companies

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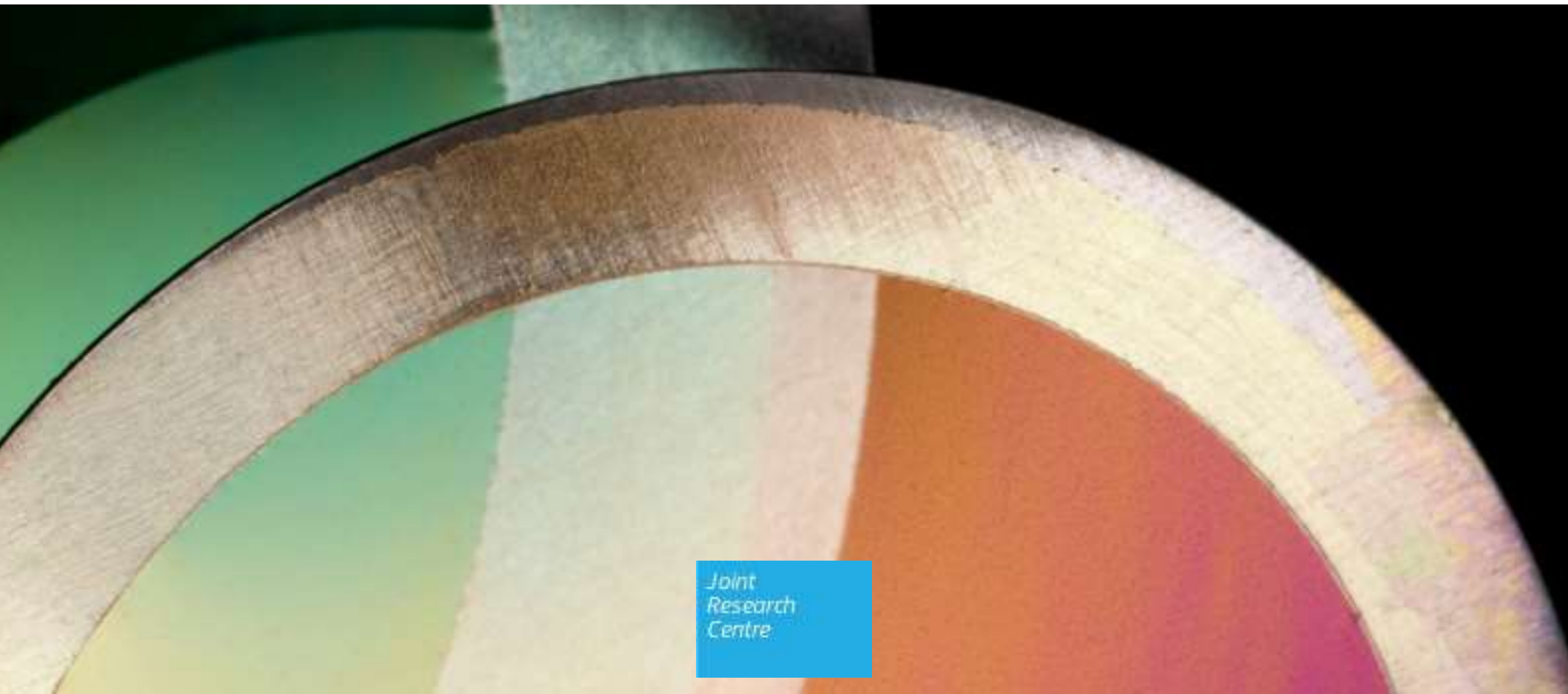

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List of abbreviations

BvD-ID	Company identification number of Orbis-Bureau van Dijk
DSM	Digital Single Market
DG-TAXUD	Directorate General Taxation and Customs Union
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
EC	European Commission
EFTA	European Free Trade Association
EPO	European Patent Office
EU	European Union
EUIPO	European Union Intellectual Property Office
GTRIC	General Trade-Related Index of Counterfeiting
ICT	Information and Communication Technology
INPADOC	International Patent Documentation
IPR	Intellectual Property Right
IV	Instrumental Variables
JPO	Japan Patent Office
JRC	Joint Research Centre of the European Commission
NACE	Nomenclature of Economic Activities
OECD	Organization for Economic Co-operation and Development
OHIM	Office for Harmonisation in the Internal Market
OLS	Ordinary Least Square
PCT	Patent Cooperation Treaty
PSM	Propensity Score Matching
ROA	Return on Assets
SME	Small Medium Enterprise
USPTO	United States Patent and Trademark Office
WCO	World Custom Organization
WIPO	Worldwide International Patent Office

Executive summary

Counterfeiting activities target companies in various sectors, including digital technology companies, 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.

Counterfeiting is a fraudulent activity that potentially damages the economic and innovation performance of companies and can pose major threats to global competition and economic growth. However, the actual impact of counterfeiting on the performance of companies has not been tested empirically, due to methodological problems, including the lack of data on counterfeiting at the firm-level. Furthermore, prior theoretical studies have speculated that counterfeiting could have in part a beneficial effect on the performance of companies, due to indirect advertising, calling for empirical investigations to shed light on the issue.

The goal of the present study is to provide empirical evidence on the impact of counterfeiting on both the economic and innovative performance of digital technology companies at the firm-level and on the global scale. To this aim, a new database was created combining data on counterfeiting activities during 2011-2013 (OECD-EUIPO, 2016) with financial information and patent data from 2009 to 2015. The result is a firm-level database that enables unprecedented analyses on the impact of counterfeiting on performance of digital technology companies.

About 9% of the seizures of counterfeits that were illegally traded across borders during 2011-2013 involved goods commercialized by digital technology companies, equivalent to about the 9.1% of the total value of seizures. Collectively, about 11% of companies affected by illegal international trade of counterfeits are digital technology companies. The majority of these (58%) are big corporations with Operating Revenues greater than USD 1 bn. These account for 77% of the number of total seizures, and 84% of the value of seizures related to the digital technology companies. SMEs, defined as those with Operating Revenues up to USD 50 million, represent 21% of digital technology companies targeted and account for 5% of total seizures and 6% of the total value of seizures.

The industries mostly targeted are electronics (both consumers’ electronics and electronics for industrial use), automotive and digital media. The digital technology products commercialized in frauds of IPRs include computer hardware and electronic components, batteries, sensors, auto-parts, optical instruments, videogames, and recording of movies and motion picture.

About 34% of digital technology companies affected by international trade of counterfeits are located in the EU28 or EFTA, 41% are located in North America, 23% are located in Asia. Within the EU28, UK, Germany, France and Italy are the countries hosting the largest number of targeted digital technology companies. Within the EU28, Germany and UK, followed by Belgium and Ireland, are the most-common country of destination of seized counterfeits.

The overwhelming majority of seized goods related to digital technology companies is imported from Asia. 51% of these are imported from China, 41% comes from Hong Kong, China, 3% from Singapore. Other economies of provenance account each for less than 1% of the seizures.

The vast majority (93%) of seizures affecting digital technology companies are due to violations of trademarks, and only a minority are due to violations of design models (4%), and copyrights (2%). Less than 1% of the seizures are due to violations of patents. However, seizures enacted in defence of patents are those that have the highest mean value.

The analysis of infringed companies with respect to a control samples of non-infringed companies indicates that counterfeiting targets specifically highly profitable companies, with high propensity to innovate. Indeed, digital technology companies are more likely to become target of counterfeiting when they have larger Operating Revenues, and when they perform at a higher level in terms of profitability (return on total assets), prior to the window of observation. Target companies also have on average larger patent portfolios, prior to the observation of counterfeiting activities.

Digital technology companies located in EU28 are on average less likely than companies located outside of EU28 to be the target of counterfeiting activities.

Results from impact analyses indicate lower growth rates of operating profits for digital technology companies targeted by counterfeiting with respect to control samples of firms not affected by counterfeiting. In particular the econometric models provide evidence of a negative impact of counterfeiting on both EBITDA (Earnings before interest taxes depreciation and amortisation) and EBIT (Earnings before interest taxes).

This result is robust across different estimation methods, model specifications and time windows. The data reveals only a weak negative impact on operating revenues, with limited statistical confidence. Conversely, there is no significant evidence that counterfeiting affected the investment in Fixed Assets of targeted firms with respect to the control sample.

The results about the negative impact of counterfeiting activities on operating profits are in line with reports of greater costs incurred by these companies to enact anti-counterfeiting strategies, reported in prior descriptive literature. These practices include the broadening of product ranges, with fewer scale-economies and the enactment of anti-infringement procedures, such as ‘conspicuous packaging’, more screening and origin certifications, development of licensing downstream retailers and direct self-enforcement aimed at limiting the circulation of counterfeits.

Results do not provide support for the existence of indirect positive spillover effects, as hypothesised by the theoretical literature, according to which infringed companies might benefit from an advertising effect due to the greater diffusion of brands from the counterfeiting activities. Indeed, at least for what concerns digital technology companies, there is no evidence of any positive effect of infringement on sales of original products.

The digital technology companies that were affected by counterfeiting on average increased their patent portfolios during the observation period, but less than the digital technology companies that were not affected by counterfeiting. However, the result is not robust to the inclusion of control variables and to the adoption of alternative measures of innovation performance (Intangible Assets). It certainly merits further research, once more data on counterfeiting become available.

Overall, the results indicate that counterfeiting activities harm the economic performance of targeted digital technology companies, by eroding their operating profits. The effect on innovative performance is negative, but still inconclusive due to insufficient dataset, and cannot exclude that counterfeiting may harm the propensity to innovate of digital technology companies. The analysis rules-out the existence of any positive spillover from counterfeiting.

1 Introduction

1.1 Background of the study

Counterfeits are fraudulent tangible goods that infringe trademarks, design rights, patents or other Intellectual Property Rights (IPRs).[1] Trading of counterfeit products is an illegal activity that poses major threats to global competition and economic growth (Staake et al., 2009; Li and Yi, 2017; Bosworth, 2006; Peitz and Waelbroeck, 2006). It is an IPR violation that potentially causes missing revenues and reduced profits to companies that are the legitimate owners of IPRs and consequently reduces government income taxes. It can also pose potential threats to the health and wellbeing of citizens and aliments criminal activity. Furthermore, the presence of significant counterfeit activity of products covered by IPRs has also detrimental effects on the incentives of companies to innovate (Peitz and Waelbroeck, 2006).

A recent study conducted by the OECD with the EUIPO has provided a global quantitative account of the phenomenon, indicating that in 2013 counterfeited goods amounted to 2.5% of world trade. The study showed that several EU economies are heavily affected by the phenomenon, suggesting that the incidence of counterfeits on the total imports was double in the EU (2.5%) compared to the total world figures and pointing at a growing trend over a five-year period (OECD, 2009; OECD-EUIPO, 2016). In a germane study, the OECD has investigated counterfeit trade in the ICT sector and has found that this accounts for about USD 143 bn in 2013, equivalent to the 6.5% of the total ICT trade (OECD, 2017).

The globalization of trade across markets and economies, with increased levels of import/export, exposes economies to a greater risk of vulnerability to IPR frauds. The potential damages of illicit trade for IPR frauds are known to be especially severe for those economies – like the European Economic Area (EEA)- characterized by a considerable propensity to innovate and generate creative contents and solutions for at least three reasons. First, the competition in industries with a strong innovative potential relies more directly on IPR-based strategies, making these businesses more exposed to suffer direct losses from infringements. Second, the value of innovative businesses relies especially on Intangible Assets, such as brands, patents, design rights, hence counterfeits undermine the market valuation of these businesses. Third, the expectation of IPR infringements potentially discourages companies from making investments in Intangible Assets, diminishing the overall propensity of the companies to invest in innovation and ultimately undermining their long-term competitive advantage.

The creation of a Digital Single Market (DSM) within the EU has among its aims that of designing the ideal environment for companies grounding their strategy and wealth on digital technologies and innovation to develop, prosper and create jobs now and in the future (European Commission, 2016). In this respect, the evidence of a high and growing incidence of counterfeits in the EEA, combined with the evidence of considerable counterfeiting activities in the ICT sector, raises concerns and demands a careful monitoring not only of counterfeiting activities, but also of the impact of counterfeiting on the prosperity and innovativeness of digital technology companies.

[1] By following the approach presented in the previous OECD studies (OECD, 2008; OECD-EUIPO, 2016), the term "counterfeit" to describe tangible goods that infringe trademarks, patents, design rights or copyrights. This does not constitute any sort of definition outside the scope of this study.

1.2 Goal of the study

The goal of this study is to produce evidence-based estimates concerning the impact of counterfeiting activities on the *economic and innovative performance* of digital technology companies. Digital technology companies are defined as those *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 study exploits the potential offered by the information on counterfeit goods seized by customs worldwide, as available from the OECD-EUIPO database, but it expands the analysis by looking at the *implications* of counterfeits for digital technology companies. Compared to the extant studies, the present study involves the adoption of a *firm-level unit of analysis*, instead of a country or industry-level and a global scale. The study monitors specifically the performance of the digital technology companies with a track record for being affected by counterfeits, with the aim to estimate the impact of counterfeiting on observable firm performance.

1.3 Methodological challenges

The choice of a firm-level unit of analysis poses significant methodological challenges. A first problem relates to identifying digital technology companies that suffered infringement. The OECD-EUIPO database stores information by seizure provided by custom authorities. For a subset of these seizures for which the violation related clearly to one specific brand or IPR, the OECD-EUIPO database provides the indication of the legitimate owners of the IPRs being violating, but this information is available only in the form of a company name and country, in string format and the only industry-relevant information provided concerns the type of goods seized (HS class 2-digits). This required a tailored methodology for identifying and extrapolating digital technology companies from the general sample, which employed a combination of taxonomy-based screening, content-analysis and manual coding. A second problem relates to tracking and matching each company in external databases, to retrieve yearly financial information and patent activity. Specifically, the information was searched by using name-matching algorithms with three external databases: Orbis-Bureau van Dijk (®Elsevier), Clarivate (®Thomson Reuters) and EIKON-Datastream (®Thomson Reuters).

The goal of assessing the impact poses further methodological issues. First, the circumstance that the targets of counterfeiters tend to be among the highest-performers in their business poses a problem of endogeneity (positive selection into treatment) that may confound the impact analysis. Second, the potential existence of trends and other unobserved factors poses a problem of spurious causality in isolating a differential impact. To partly overcome these challenges, the study adopts a pool of estimation techniques, used in alternative, that include matching-pairs, difference-in-difference and instrumental variables estimates.

In summary, the present study aims at assessing the impact of counterfeiting activities on the economic and innovative performance of digital technology companies. The study relies on creating a new firm-level database, which is unique of its kind and requires the use of a broad set of statistics and econometric techniques of impact analysis.

2 Review of the literature

Previous studies have analysed the phenomenon of counterfeit trade along different perspectives. In light of the scope of this project, and in accordance with recent scientific works (Staake et al., 2009; Li and Yi, 2017; Peitz and Waelbroeck, 2006), this literature review is organized by subject. First, it reviews the studies that have dealt with measuring the phenomenon of counterfeit trade and provides an overview of the most recent figures. Second, it reviews the theories and empirical findings on the implication of counterfeiting for the main stakeholders, with a focus on firm performance.

2.1 Measuring counterfeit

In recent years, international organizations and governmental agencies have been concerned with providing an estimate of the counterfeit trade on a global scale, with the goal to appreciate the actual extent of counterfeiting in terms of total amount and value of counterfeit sales, percentage of counterfeit trade over licit trade, and market shares of counterfeits.

Estimating the actual extent of counterfeiting is nonetheless a challenging task due to the illicit nature of the phenomenon, which enables only limited and partial observability.

Existing studies have attempted to measure counterfeiting using a range of data sources that include custom seizures, seizures of production facilities, comparative analyses of total demand and total supply, and consumers' surveys (BSA, 2016; OECD, 2008; OECD-EUIPO, 2016). Unfortunately, many of these methods are unsuitable to be applied on a pervasive and global scale. Amid data shortage, custom seizures of counterfeited goods have progressively emerged as the most comprehensive and reliable source of data (Staake et al., 2009), albeit not exempt from limitations.[2] Because data on seizures represent only a fraction of total counterfeit trade, estimating the overall incidence of counterfeits in the economy requires additional statistical processing (European Commission 2012). Using statistical inference on a dataset of German custom data in which each item seized is classified as being either authentic or counterfeit at the inspection, Cuntz (2016) estimates that the range of counterfeit goods in the German economy in 2010–11 was ranging between a 9,5 and 22 percent of total import.

An alternative approach consists in computing indexes of the relative propensity to import counterfeit products, based on the relative incidence of counterfeits among the trade partners and on the relative incidence of counterfeits among the product categories traded. These indexes are called GTRIC and are developed and maintained by the OECD (OECD-EUIPO, 2016).

The most recent and comprehensive work that estimated the size of counterfeit trade by applying this methodology to custom seizures has been carried out in the OECD - EUIPO study (OECD-EUIPO, 2016). The database used for the study assembled information on seizures of counterfeit products from three sources: The World Customs Organization (WCO), the European Commission's Directorate-General for Taxation and Customs Union (DG TAXUD), and the United States Department of Homeland Security (DHS). The OECD-EUIPO database contains half a million custom seizure data covering the period of 2011-13 and the last available year is 2013. According to the OECD-EUIPO estimate, the trade in counterfeit and pirated goods is estimated to account for as much as 2.5% of world trade, or 5% if restricted to trade related to the EU countries.

[2] First, counterfeit goods that are seized at the custom represent only an unknown share of the total counterfeits that are illegally traded across the borders, and do not account for trade of counterfeits that does not travel across the borders. Second, custom controls that eventually result in seizures are not necessarily random and may rather reflect priorities of the country and the authorities, such as the need to prevent the spread of products that may potentially pose threats to the health of citizens. Third, collection of seizures data is normally conducted for reasons different from statistical computation and by individuals that have no training in statistics. Forth, products that infringe trademarks are relatively easier to be detected by custom officers compared to products that infringe on other Intellectual Property Rights (IPR), such as patents or copyrights (Berger et al., 2012).

The OECD-EUIPO estimate highlights a growing trend in counterfeit trade, considering that the counterfeit trade was estimated to be 1.9% of world trade in 2008. The growing trend finds confirmation in other reports. In terms of annual losses, counterfeits were estimated to imply a loss of around USD 10-30 bn in the early 1980s and the same figure had reached more than USD 200 bn by the end of the 2000s (Wilson and Sullivan, 2016)[3]. Furthermore, the number of applications for action filed and applicable in the member states has tripled in the last decennium (European Commission, 2016b).

Concerning the geographic dimension of the phenomenon, the study by OECD-EUIPO (2017) shows that nearly 20% of the seizures in value are for goods whose owners reside in the US. Other heavily targeted economies are Italy, France, Switzerland, Japan and Germany. Middle-income and emerging economies play an important role either as transit points in international trade (e.g. Hong Kong, China, the United Arab Emirates and Singapore), or as producing economies (e.g. China, India, Thailand, Turkey, Malaysia, Pakistan and Viet Nam). China is the largest producer of counterfeits, even if Chinese brand owners are also frequently targeted.

According to the recent report of Europol-OHIM (2017), Free Trade Zones are associated with a high number of IPR crimes. EU-based criminals rely predominantly on manufacturers based abroad, but the organisations for the import, storage and distribution of the counterfeit goods are based within the EU. The Europol-OHIM report (2017) also highlights the presence of potential new threats in the IPR crime landscape deriving from the increasing use of rail transport as a method of cargo conveyance between China and the EU.

The target of counterfeits are primarily branded products, and more generally those products with a low-price elasticity generated by the presence of IPRs (Berger et al., 2012). Counterfeits exist in almost all sectors, from luxury products (e.g. watches, fashion bags), to products of common consumption (e.g. cigarettes), and include products for business goods (e.g. tyres) and technology products (e.g. hard disk drives).

The counterfeit goods related to the ICT sector have been estimated to account for USD 143 bn in 2013, equivalent to the 6.5% of the total ICT trade and significantly more than the general average (OECD, 2017). Memory sticks, solid state drives, sound apparatus and video games are among the most frequent type of ICT goods seized at customs. The statistics for the ICT sector show that companies located in the US, Finland, Japan, Korea, and Germany are those reporting the highest number of cases of infringement (OECD, 2017).

Looking jointly at geography and product categories, some economies appear as specialized in the illicit traffic of specific goods: Benin for food, Mexico for alcoholic beverages, Morocco for other beverages, Malaysia for body care items, Turkey for clothing, Hong Kong, China, for mobile phones and accessories, memory cards, computer equipment, CD/DVD and lighters, Montenegro for cigarettes and India for medicines (European Commission, 2016).

Concerning the organization of the counterfeit trade, the studies suggest that the largest share of counterfeit goods are shipped in containers over long distances and are later distributed in smaller parcels by post or by courier services. Sometimes fake labels and fake packaging are shipped separately from the counterfeit item and assembled at destination. This trading system is fostered by the reduced costs of postal and courier shipments and the increasing importance of Internet and e-commerce in international trade. Small shipments with fewer than ten items accounted for about 43% of all shipments, on average (OECD-EUIPO, 2017). The use of small batches is particularly evident in the counterfeiting of ICT goods, where two thirds of shipments are done through post or by couriers.

An alternative approach to estimate counterfeit at the economy level is employed in Pacula et al. (2012). The authors rely on confidential aggregated product-level data to assess industry-specific counterfeiting activities in various geographic markets. While this type of study can provide interesting insight about the perceived impact at the firm of counterfeit, the

[3] Note that the accuracy of these estimates in some cases have been challenged (US Government Accountability Office, 2010; Wilson et al., 2016).

methodological approach is not appropriated for the estimation of the aggregated size of the counterfeit phenomenon.

Additional methods have included surveys of supply and demand (e.g., Rob and Waldfogel, 2006), economic multipliers to estimate the effects on the U.S. economy (e.g., Siwek, 2007), statistical modelling (e.g. Oberholzer-Gee and Strumpf, 2009). The report by the European Commission (2012) provides a comprehensive discussion of the alternative approaches and technical issues for the generation of aggregate estimates of counterfeit.

2.2 Impact of counterfeiting

One area of direct interest for the present analysis concerns the economic implications of counterfeiting. In this area, there are several works from industry, institutional, and government entities (e.g. International Chamber of Commerce, 2006; European Commission, 2016; OECD-EUIPO, 2016; WIPO, 2010), as well as academic studies (e.g. Staake et al., 2009; Li and Yi, 2017; Peitz and Waelbroeck, 2006). Overall, the works have investigated the potential consequences of counterfeits from both the theoretical and empirical points of view and have used both quantitative and qualitative methodologies.

The literature has highlighted that counterfeits produce a number of multifaceted consequences on the market of genuine goods that have implications for companies, but also for consumers and for the economic system at large (Staake et al., 2009; WIPO, 2010). The next paragraphs provides an overview and common ground on the welfare impact on counterfeiting and further expands the analysis by looking at the different perspectives of infringed firms, consumers, and government.

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 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 Asset and by imposing losses of value to those consumers that have unwittingly purchased copies. They also stress that counterfeit potentially alters the behaviour of infringed firms, which 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 general, they predict that counterfeiting produces a welfare reduction in markets with free entry, whereas the predictions are not univocal for markets with a fixed number of competitors.

It is worth noting that a general welfare reduction is not necessarily true in markets characterized by strong network externalities or bandwagon effects (Conner and Rumelt, 1991). In these markets, there is a positive externality for producers and consumers of original products, because customers' utility is an increasing function of the users' base. Conner and Rumelt, (1991) find that, although software piracy generally harms both software firms (reducing profits) and customers (increasing prices), firms and customers could gain a positive network externality effect when the lower prices of counterfeits enables a more widespread adoption of a product (see also Givon et al., 1995, and Shi et al., 2016). Under these circumstances it is possible that the externality effect in the long term generates an increase in the demand, especially in the case of luxury goods and in brand-related business ventures (Nia and Zaichkowsky, 2000; Bekir et al, 2013; Li and Yi, 2017). One classical example is the market of the operative systems and the related software, in which it is possible that pirated software availability have indirectly contributed to consolidate the use of Microsoft windows products (Qian, 2014). More complex effects were found by Jaisingh (2009) who suggests the social planner to adapt the policy rules according to the presence of monopoly or competitive market, since in the former an increase in the severity of the anti-counterfeit laws and procedures could provide a disincentive for innovation.

One important distinction that emerges in the literature relates to "deceptive" versus "non-deceptive" counterfeits. Deceptive counterfeits are copies that aim at confusing consumers, making them believe that they are buying the legitimate product. In this case, the counterfeit is traded in the legitimate market, which is termed in this literature as "primary market" of counterfeiting (OECD, 2008).

Primary market purchase implies that deceived consumers buy at prices equal or almost equal to those of the original products. Therefore, purchase of deceptive counterfeits can be considered as largely replacing the purchase of original products, resulting in a direct damage to the legitimate producer. As a consequence, with deceptive counterfeiting, the incentives for producers to invest in high value products are potentially undermined, challenging the very existence of high-quality and innovative markets. Furthermore, rational consumers aware of the presence of fake goods on the market, even if unable to distinguish fakes from original products, would have been unwilling to pay the full price of a high-quality good for the fake. Therefore, deceived consumers typically receive products with a value well below the price they would have paid if they knew that the product was fake. As a consequence, with deceptive counterfeiting, the consumer suffers a loss of product value. Furthermore, they suffer the loss of after-sales services (e.g. guarantee, customer care).

Non-deceptive counterfeits are instead copies which are commercialized as clear fakes. In this case the copies are purchased by aware customers in what are called by this literature "secondary market" of counterfeiting (OECD, 2008). Secondary markets offer counterfeit products at prices much lower than the original good prices. Therefore, it is legitimate to believe that purchases of these goods do not or only partly replace purchases of genuine goods. However, for luxury products, for which part of the value depends on the status associated to the limited circulation of the products (also called 'status goods'), the display of the product's or the producer's name may confer prestige to the purchaser, yielding utility independent from the utility derived from the goods' physical or functional characteristics and without paying the related price. As a consequence, consumption of deceptive counterfeits may create an indirect damage in terms of company brand value. At the same time, circulation of copies may also create an indirect 'advertising effect' that potentially affects brand value positively. At the same time, consumers of the counterfeit product experience a partial loss of status, and consumers and producers of counterfeits obtain an unfair benefit.

The overall effect on social welfare depends on the values of the relevant market parameters and remains an open problem to be answered by empirical investigations (Grossman and Shapiro, 1988b).

2.3 The perspective of infringed firms

This stream of works has investigated the response of original producers to the challenge posed by counterfeited products with the aim of understanding the strategies enacted in response to counterfeits (including innovation) and the overall impact of counterfeits on the economic and financial activities of the firm. Here, as before, the paucity of data, particularly at the firm and product level, has traditionally been an obstacle to perform large-scale empirical investigations. In addition, these analyses are complicated by the endogeneity of the counterfeiting activities with regard to firm performance, i.e. counterfeiters typically copy successful/ high-performing products and profitable brands (Berger et al., 2012). As a consequence, only a small number of studies has assessed the effect of counterfeits empirically.

Among the early work conducted at the firm level, Feinberg and Rousslang (1990) examine the welfare effects of foreign IPRs (trademark, copyright, or patent) infringements among US companies. Although they do not specifically focus on counterfeit trade, they find that profit losses are at least as great as 1% of the total sales and expenditures on counter-measures are about 4% of the losses. In fact, companies facing the threat of counterfeiters are reported to enact anti-counterfeiting strategies and practices which increase costs (Staake et al., 2009; Li and Yi, 2017).

In a series of studies, Qian (2008, 2012, 2014) 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. Making use of firm-product-level data combined with surveys, the author investigates the response of companies to counterfeiting. She maintains that original producers facing counterfeiting put in action strategies to differentiate their products from copies and to increase the level of control of the product circulation in the final market. For example, in the Chinese shoes market, the companies targeted by counterfeits differentiated their products through innovation, self-enforcement, vertical integration, and subtle high-price signals in response to counterfeit entry. Collectively, these strategies are costly to the company and push the prices up. When she instruments the analysis to eliminate the effects of possible endogeneity, she finds that the entry of counterfeiting has a twofold effect: increasing market prices of original goods pushed by an increase of costs and reducing counterfeit sales. The increase in prices of the original product estimated in the Chinese shoes market two years after the entry of counterfeiters was as much as +45%. The estimated impact of counterfeiting entry on the profit of original producers is negative, but not statistically significant (Qian, 2008). Export is also not affected.

Qian and Xie (2010) find that, in some cases the price response to counterfeiting entry can be more complex and change over time. Specifically, counterfeiters' entry may push the original producer to reduce prices at first, and later increase the quality differentiation which subsequently drives the prices up. This increase happens at different times for different firms. Larger firms with more human capital and research and development resources respond faster compared to smaller firms. Furthermore, with different penetration of counterfeits in different markets, the response time can also be influenced by geographic composition of the sales.

An important aspect of Qian's finding relates to showing that the competition brought to the market by the entry of counterfeiters forces the original producers to invest in the differentiation of the original product. For example, she finds that the material and design, as well as the technological equipment used by original manufacturers in China improved in response to the entry of counterfeits, raising the overall quality of the shoes of +15%. As a consequence, product innovation might increase –instead of decreasing- in response to the entry of a counterfeiters.

Box 2.3 Anti-counterfeiting strategies

Companies that are under the attack of counterfeiters can react to the threat in different ways. The range of possible actions that have been reported by the original producers include:

- Investing in product attributes that are difficult to imitate, including quality and technology (conspicuous products)
- Increasing prices to signal quality
- Investing in advertising
- Improving packaging, including difficult-to-copy labels and certificates of authenticity (conspicuous packaging)
- Investing in vertical integration with downstream retailers (licensed brand stores)
- Enacting self-enforcement policies, including private investigations, and training of retailers and custom authorities.

Collectively, these strategies are meant to differentiate the original product from the counterfeits and make the counterfeits more easily identifiable to the retailers, the customers, and the authorities. The strategies are costly for the companies and the product differentiation that they produce is not necessarily welfare-enhancing, as if the costs incurred were invested to innovate.

The finding is consistent with the works of Feinberg and Rousslang (1990) and of Liebowitz (2005), who observed that original producers respond with differentiation through quality improvements. Further confirmation come from the analysis of piracy, where the increase in product differentiation and innovation is termed 'piracy paradox' (Raustiala and Springman, 2009). Although these investments in innovation are provoked by an unfair competition and might also not be welfare-enhancing (WIPO, 2010), their existence is important to bear in mind from a methodological point of view, because they could exert a potential confounding effect that counterbalances the expected decrease in the incentives to innovate induced by IPR expropriation.

Berger et al. (2012) investigate which companies potentially face higher risks of suffering IPR infringement by running and analysing an original survey in various sectors. They show, among other findings, that companies with higher investments in IPRs and stronger brands are more exposed to imitation, confirming the preference of counterfeiters for stronger and more popular brands.

Among the additional costs that original producers might sustain when facing counterfeiters, the literature has highlighted that companies invest in the implementation of advanced technologies and techniques, like RFID, watermarking, shipment inspection procedures (Holliman and Memon, 2000; Siror et al., 2010; Li, 2013). Particular attention has been given in the literature to the detection of specific pharmaceutical compounds (e.g. Deisingh, 2005) and the impact of counterfeited integrated chips along the supply chain (Guin et al., 2014). Other costs in cases of counterfeit occurrence consist in the establishment of enforcement measures and potential liability claims in cases of health and safety hazards for consumers (Feinberg and Rousslang, 1990; Liebowitz, 2005).

As mentioned earlier, counterfeit goods potentially affect the value of the copied brand and the overall firm reputation. In this respect, many studies suggest that counterfeits reduce brand equity, especially for luxury goods (Gabrielli et al., 2012). The reason is that illicit goods are usually of lower quality, which damages the overall attractiveness 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). Furthermore, 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).

Concerning the strategies enacted to detect counterfeiting, the literature has reported that many companies screen the market actively (Wilson and Sullivan, 2016). Many have started to do so after facing losses in sales, receiving quality complains and returns from deceived customers, or when alerted by third party or by large incidents of trademark infringement (Green and Smith, 2002; Chaudhry and Zimmerman, 2009; Reynolds, 2011).

2.4 The perspective of consumers

Several scholars have investigated consumer behaviour and attitudes in the presence of counterfeit goods with the aim to improve the understanding of the traits of customers, the rationale for their choices, ethics, and morality. Most of the studies in this area rely on surveys administered directly to consumers or to experts in the field (e.g. Nia and Zaichkowsky, 2000; Ang et al. 2001; Cordell et al., 1996; Wilcox et al., 2009).

The works identified negative implications for the consumers both in the case of deceptive and non-deceptive counterfeits. In the former case (i.e. "primary market" counterfeiting), consumers purchase products with a lower than expected value (Grossman and Shapiro, 1988a and 1988b) and experience a loss of rights such as guarantee, customer assistance, etc. When considering special types of products (e.g. pharmaceutical, batteries, etc.), the purchase of fake goods may pose health and safety hazards (Feinberg and Rousslang, 1990).

When focusing on the non-deceptive informed sales (i.e. the "secondary market" counterfeiting), the consumers experience a mixed effect: on the one side, they enjoy the status without paying the price of the original good, but on the other side, the marginal value deriving from the exclusivity is reduced due to the greater club size. The overall effect on social welfare depends on the values of the relevant market parameters (Grossman and Shapiro, 1988b).

Further indirect positive effects for the consumers might be related to a price reduction in specific cases (Li and Yi, 2017), even if this could be only temporary (Qian and Xie, 2010). Differently from status goods, in the case of software, a price reduction could increase the number of users and generate positive network externalities (Conner and Rumelt, 1991; Givon et al., 1995; Shi et al., 2016).

2.5 The perspective of national governments

Counterfeit trade is an illicit activity that generates losses in tax revenues and employment, raise IP enforcement expenses, reduces investments in innovation and hinders the development, growth, and competitiveness of the products (Feinberg and Rousslang, 1990; Liebowitz, 2005; Li and Yi, 2017).

Furthermore, some counterfeit goods like pharmaceuticals, batteries, or toys, may pose additional health safety hazards for consumers. Finally, the profits from sales of counterfeit and pirated goods may very often serve to finance other criminal activities (WIPO, 2010; Europol-OHIM, 2017).

Previous literature reviewed measures for contrasting counterfeit and piracy in a qualitative way, for example, educating consumers and raising public awareness about the harmful effects of counterfeit (Chiu et al., 2008; Li and Yi, 2017); protecting IPRs through patents, copyrights, and trademarks (Bell and Parchomovsky, 2005); strengthening the enforcement of IPRs (Olsen and Granzin, 1992); or inspections along supply chains.

The existence of potentially positive spillovers from counterfeiting activities for governments have not been sufficiently investigated so far and no formal modelling has been developed concerning the long-term perspective (WIPO, 2010). However, McDonald and Roberts (1994) proposed that counterfeit trade may increase the transfer of technology to less developed economies and the general satisfaction of market needs, which on the long-term may reduce the negative effects of the phenomenon.

In conclusion, a rather limited number of studies has dealt with the impact of counterfeit trade on infringed firms and only a few studies have performed empirical investigations, due to a lack of reliable firm-level data. At the theoretical level, both deceptive and non-deceptive counterfeiting can harm companies by reducing their sales and increasing their costs. Furthermore, counterfeits can lower the value of brands and the incentives of companies to invest in innovation. However, these predictions lack substantial empirical evidence. The companies targeted by counterfeiting have been found to respond to the threat by enacting anti-counterfeiting strategies and practices that can range from product differentiation, and increased advertising, to conspicuous packaging, vertical integration with downstream retailers, and direct self-enforcement. Again, these practices have been documented on specific cases, but no large-scale study exists.

However, the theoretical literature has also hypothesised the existence of positive spillovers caused by counterfeiting for companies, potentially due to indirect advertising received from fake products and/or widespread distribution in markets with strong network externalities. These hypotheses have never been tested empirically and further restate the need for rigorous empirical analyses at the firm-level, which are among the goals of this study.

3 Firm-level database

The firm-level database used for the analysis is a relational database organized at the company-level, where each record identifies univocally a digital technology company. Digital technology companies in this report are defined as those *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 strategy for constructing the database is coherent with such definition.

3.1 Information sources

The database used for the study results from the combined information from multiple data sources.

OECD-EUIPO database. The database was used as the source of information on IPR owners and economies, and on numbers and values of custom seizures registered in 2011, 2012 and 2013 in 92 economies around the world (including all the EU countries, US, Japan, and Korea among others). It also provided information about the categories of goods seized (based on the Harmonized System and Combined Nomenclature taxonomies).

Orbis-Bureau van Dijk (®Elsevier) and **EIKON Datastream** (®Thomson Reuters). These databases served as sources of financial and economic information originated from balance sheet data. The BvD-ID (from Orbis-Bureau van Dijk) was used as the primary key linking the information across the relational database.

Clarivate Analytics (®Thomson Reuters). The database was used as the source of data on patent applications and grants.

Retrieval of information and data consolidation was performed between August and December 2017.

3.2 Retrieval and match of companies from OECD-EUIPO

The OECD-EUIPO database was the source of a number of information used to identify the companies whose IPRs had been infringed: The name of the IPR owner, the country of the IPR owner, the country of origin and destination of the seized goods, a short textual description of the good seized (e.g. "Electronic toys"), the Harmonized System (HS) classification, the brand of the seized good, and whether or not the company was coded as ICT (OECD, 2017).[4]

3.2.1 Selection of digital technology companies

The first methodological concern that emerged was related to the identification of the subset of counterfeits related to digital companies, defined, in this study, 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.*

This definition includes companies that produce and/or commercialize consumers electronics (e.g. cell phones, computer equipment, smart watches, etc.), electronic components (e.g. sensors, microchips, displays, remote controlling, etc.), audio-visual content stored on physical digital support (e.g. producers of music, films, digital animation movies, etc.), and complex

[4] To comply with the confidentiality requirements, the OECD-EUIPO was accessed only at the OECD premises, by the OECD Secretariat.

products that incorporate physical digital components (e.g. automotive companies producing sensors for assisted driving, etc.). 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 merchandize (e.g. football clubs that commercialize a digital watch with the name of the team).

To select digital technology companies, a three steps procedure was followed. The first step consisted in including all potential digital companies based on the information about the Harmonized System (HS) classification included in the OECD-EUIPO database[5]. The purpose of step one was maximum inclusion, i.e. returning a redundant set of companies in which no or very minimal incidence of false negatives (digital companies not included by mistake) was expected. At the same time, step one alone allowed for a high presence of false positives (non-digital companies included by mistake), that called for subsequent screening. Step two was meant to reduce the incidence of false positives by using a finer-grained coding (4-digit NACE), extracted from Orbis-Bureau van Dijk, after matching company names. This second filter is conservative and reduces only partially the incidence of false positives. Step three was meant to screen all the remaining instances by means of a manual screening and select only the digital technology companies for final inclusion. The three steps are described in deeper detail in the following.

3.2.2 Step 1: HS and content analysis

In order to conduct the search of digital technology companies across a very broad set of HS classes, an iterative approach was adopted. Initially, all companies whose seizures are in HS classes that are sure to include –albeit not exclusively- digital technology products were included. These are HS 84 [*Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof*] and 85 [*Electrical machinery and equipment and parts thereof; sound recorders and reproducers; television image and sound recorders and reproducers, parts and accessories of such articles*]. These two classes alone would not include other companies that fit the definition of digital technology companies and are categorized in mixed digital and non-digital HS classes. In order to broaden the pool of HS classes, a content analysis based on the verbal good descriptions of the seized good included in the OECD-EUIPO database was performed.

In particular, the content analysis procedure unfolded as follows. As a first step, a dictionary of digital-technology related terms was created, by means of a computer software developed ad-hoc. This software initially pre-processed a selected list of reports on digital technologies recently published by the European Commission[6], by applying a tokenization[7] algorithm (Mcnamee and Mayfield, 2004), which transformed the texts into a list of words ordered by frequency. After reducing inflected and derived words to their root forms with a stemming algorithm (Willett, 2006) and dropping words that do not carry meaning with a 'stop words' tool (e.g. Venkatsubramanyan and Perez-Carballo, 2004; Huang and Ng, 2006; Seroussi et al., 2012; Rathi and Twidale, 2013),[8] the software returned a word list. The word list was validated via manual expert check to ensure coherence and consistency, resulting in a list of 91 terms (words and words combinations) denoting digital technologies.

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[5] 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-digits 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-digits classes) and subheadings (6-digits classes), for a total of approximately 5.000 fine-grained categories. The OECD-EUIPO database contained information at the 2-digits level.

[6] Publications of the EC digital transformation monitor written in English were used to the aim. 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 Internet of Things (European Commission, 2016a; Friess, 2016).

[7] Tokenization is the process of dividing a text into a sequence of words

[8] http://www.lextek.com/manuals/onix/stopwords1.html, accessed on September 20, 2017

The terms of the words list were searched in the seizure description of the OECD-EUIPO database with the purpose to minimize exclusion. As an outcome to this procedure, all the HS classes where at least one term of the word list was present were flagged as potentially digital. This analysis broadened the pool of potentially-digital HS classes to comprise all classes from 84 to 92 plus the class 37. Associated to these HS classes were 73.651 seizures and 737 IPR owners, who could be potentially digital technology companies. The choice of including all the seizures associated to the HS classes identified means that the resulted company list includes at this stage a high incidence of false positive that will require subsequent selection in steps 2 and 3.

3.2.3 Step 2: First matching with Orbis

To enrich the information concerning the companies selected in step 1, the list of 737 companies was matched with related records in the Orbis-Bureau van Dijk database. The match was done based on the string of company name and country of the IPR owner and was organized into two complementary and sequential activities.

i) **Automatic -computer based- matching.** Given that the list of company names was harmonized within the OECD-EUIPO database but not harmonized with string names in Orbis-Bureau van Dijk, the matching often resulted either in an empty set or in multiple records in Orbis-Bureau van Dijk corresponding to a single entry in the OECD-EUIPO database. Approximate string matching algorithms (also known as fuzzy logic algorithms) were used to assess similarity among each potential combination, in order to select the right company[9]. For each ambiguous string, the closest string to the searched one was selected. This automatic matching was assisted by an expert to ensure the maximum fit of the matching. The result was a list of 577 matched companies.

ii) **Manual matching.** After the automatic matching, 160 companies included in the OECD-EUIPO database resulted not paired with a record in Orbis-Bureau van Dijk. An additional manual search was performed for these instances. During this activity, the focus was directed specifically to company names that, for different reasons, eluded the approximate string matching algorithm. The focus was on alias of names and acronyms, misspellings, and possible inconsistencies referring to the country of the IPR owner. Manual matching was performed only when the risk of a wrong combination was low or very low. Overall, manual matching enabled including 80 additional companies. Thus, in total, 657 companies of those in the initial list of 737 were matched, equivalent to 89.1%.

Matching of OECD-EUIPO with Orbis-Bureau van Dijk enabled associating the potential digital companies resulted from step 1 with information of Orbis-Bureau van Dijk, including the 4-digit NACE codes of the firm's industry. The 4-digit NACE provides a finer-grained classification of industries compared to the HS classification used in step 1. A list of NACE codes was created from the companies of the OECD-EUIPO database (OECD, 2017) related to digital products, as identified from the content analysis. The list was used to identify, by difference, the companies that did not have digital technology products. The excluded companies were further checked randomly to reassure that exclusion criteria did not generate false negatives.

The result of step 2 was a list 406 companies that shared at least one 4-digit NACE code either with companies coded as ICT-related or with companies whose related seizures included keywords denoting digital content.

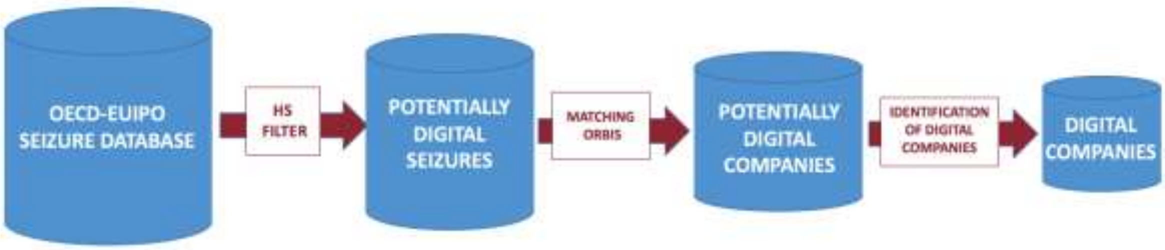
[9] Approximate string matching algorithms are a group of techniques for searching strings that match a pattern approximately, rather than exactly.

3.2.4 Step 3: Identification of digital companies

The third and final step was meant to filter-off the sample of the 406 companies resulted from steps 1-2, all the remaining companies that were arguably non-digital, based on the definition adopted. Specifically, the records were manually checked to exclude all companies not committed in the making of digital products, by screening the Orbis-Bureau van Dijk record information and at the information contained in the website of the companies.

Step 3 enabled clearing away from the sample 146 companies that resulted to be non-digital. The result was a final list of 260 digital companies that were affected by illicit international trade of counterfeit products during the period 2011-2013.
The database construction process is synthesized in Figure 1.

Figure 1 Database construction process



3.3 Data consolidation, control sample and patent data

Having defined the set of digital technology companies that were affected by counterfeiting, the analysis continued with the construction of a control sample of digital technology companies likely not affected by counterfeiting. Methodologically, this sample was selected among the companies listed in Orbis-Bureau van Dijk and not listed in the OECD-EUIPO database. Specifically, for each group of companies targeted by counterfeits with a specific combination of 4-digit NACE, geographical area and dimensional category, it was retrieved the corresponding group of companies in the same 4-digit NACE, geographical area and dimensional category that were listed in Orbis-Bureau van Dijk and not in the OECD-EUIPO database. Collectively, the search resulted in a control sample of about 29,000 companies which were included in the firm-level database.

Financial information was retrieved from Orbis-Bureau van Dijk for the 260 digital technology companies and the companies in the control sample. For those companies that were the target of counterfeiting and resulted to have incomplete financial information in Orbis-Bureau van Dijk in the years of interest, a supplementary search of data was conducted in the EIKON Datastream-Thomson Reuters database, on the basis of the name, country and NACE code. This additional datasource enabled completing missing data for 34 companies (13% of the sample of digital technology firms).

Patent application data were retrieved from Clarivate Analytics, which provides information on patent filings on a global scale. This information was retrieved for all digital technology companies that were affected by infringement and for a set of companies that represented the best one-to-one nearest-neighbour matching with replacement of the counterfeited companies (more details on the matching procedure are provided in Section 6). For the purpose of the present study only patents filed at the EPO, the USPTO, or the JPO, or through the PCT procedure were considered. Given the time frame of the data on seizures (2011-2013), priority year of target patents was restricted to be between 2009 and 2015.

The overall number of firms (either infringed or in the control sample) with at least one patent application during years 2009-2015 is equal to 249: 72,7% of the infringed firms and 75,5% of the control sample firms.

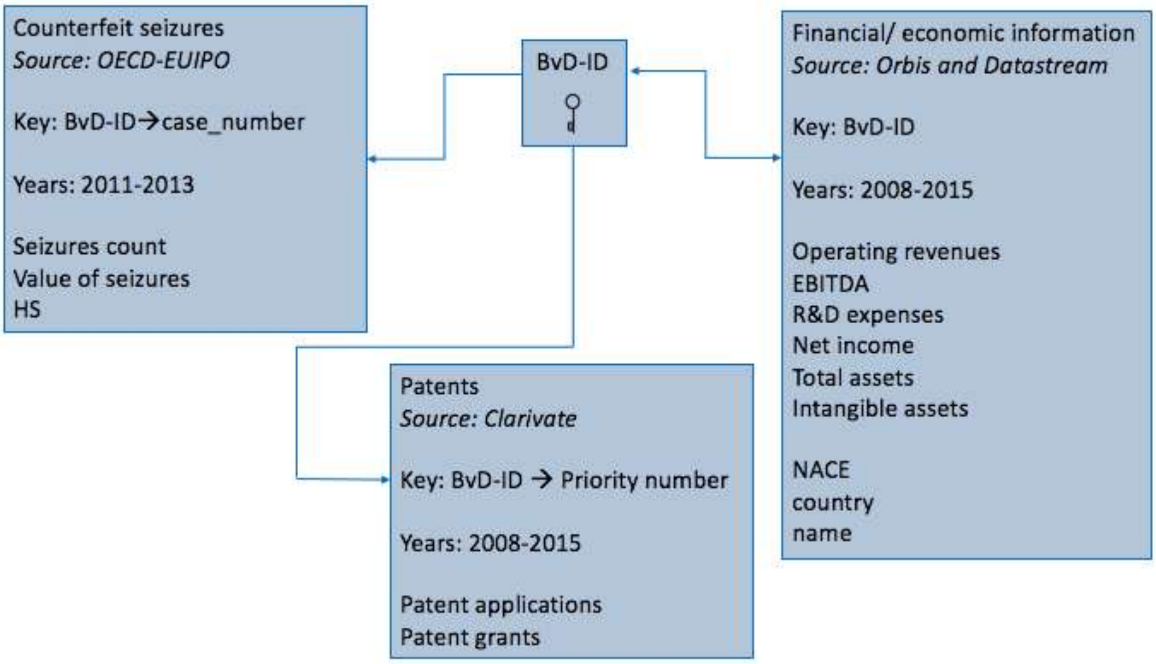
The retrieved patent records were consolidated at the level of INPADOC patent families in order to avoid the duplication of single inventions extended to multiple patent offices. Furthermore, relying on patent families provides a more accurate proxy of innovation output. It has to be recalled that new patent filings have an 18 months' period of secrecy and usually additional 12 months are required to observe them in commercial databases. Hence, more recent patent applications might be underestimated in the database. However, this data limitation is less relevant when using control samples in order to compare patent applications in a given year among subgroups.

3.4 The structure of the firm-level database

The firm-level database has a relational structure, and its primary identification key is the BvD-ID number. The structure of the database is illustrated in Figure 2. There are three main pools of data in the database. The first pool is the *Counterfeit seizures* data, and includes seizures and values of counterfeits from 2011 to 2013 for the 260 digital technology companies that were affected. The second pool is the *Financial/economic information*, and includes: identification information (legal entity name, country, NACE industry code, dimensional category), and economic and financial information from 2008 to 2015 (from Income Statements and from Balance Sheets) for both the digital technology companies subject to counterfeit and the control sample companies. The BvD-ID identifier enables subsequent matching with additional information. The third pool is the *Patent information,* and includes the number of patents filed with an earliest priority between 2009 and 2015 by the digital technology companies subject to counterfeit and their one-to-one nearest neighbour pair.

The process of database creation relied on a correspondence table associating the BvD-ID of digital companies with the seizure case number (primary ID of the OECD-EUIPO database), based on the harmonized company name of the OECD-EUIPO database.

Figure 2. Structure of the firm-level database



3.5 Information coverage

Information concerning the economic and financial activities of the digital technology companies was collected for the accounting years 2008-2015, as available in the database Orbis-Bureau van Dijk. Given the relatively-high incidence of missing data found in the series, economic and financial information were integrated by means of the database EIKON Datastream (Thomson/Reuters®), which contains data for firms in 400 exchanges and OTC-traded markets.

Table 1 reports a summary of the observations available for a selection of the most important annual indicators used in the subsequent analysis. As the data evidence, the incidence of missing instances is considerable for the years of interest. This has implications for the data analysis. First, the number of usable information varies across models, depending on the variables and years used in the model. Second, some information, notably R&D expenses, exhibited a very high incidence of missing values, despite the considerable data integration. This is due in part to imperfect data coverage in the source databases and in part to the different accounting regulations concerning R&D expenditures that exist in different economies. As a consequence, the analysis that follows could not take into account R&D expenditures, despite their potential relevance to the analysis, because of the limited coverage of this information in the firm-level database. Concerning the information on patenting activities from the database Clarivate, no significant lack of data is observed.

Table 1. Availability of information for digital technology companies. Affected companies (selected items and years)

Variable	Observations	Missing	% coverage
Net income 2010	133	127	51.2%
Net income 2011	137	123	52.7%
Net income 2012	142	118	54.6%
Net income 2013	145	115	55.8%
Net income 2014	141	119	54.2%
Net income 2015	139	121	53.5%
Operating revenues turnover 2010	134	126	51.5%
Operating revenues turnover 2011	141	119	54.2%
Operating revenues turnover 2012	144	116	55.4%
Operating revenues turnover 2013	146	114	56.2%
Operating revenues turnover 2014	144	116	55.4%
Operating revenues turnover 2015	145	115	55.8%
Intangible Fixed Assets 2010	164	96	63.1%
Intangible Fixed Assets 2011	170	90	65.4%
Intangible Fixed Assets 2012	175	85	67.3%
Intangible Fixed Assets 2013	178	82	68.5%
Intangible Fixed Assets 2014	175	85	67.3%
Intangible Fixed Assets 2015	169	91	65.0%
Total assets 2010	170	90	65.4%
Total assets 2011	173	87	66.5%
Total assets 2012	177	83	68.1%
Total assets 2013	181	79	69.6%
Total assets 2014	177	83	68.1%
Total assets 2015	175	85	67.3%
R&D expenses 2010	91	169	35.0%
R&D expenses 2011	88	172	33.8%
R&D expenses 2012	90	170	34.6%
R&D expenses 2013	89	171	34.2%
R&D expenses 2014	86	174	33.1%
R&D expenses 2015	83	177	31.9%

3.5.1 Other methodological caveats

There are other methodological caveats to be considered before using the firm-level database.

First, the imperfect coverage of information in the data-sources may cause sample selection issues that cannot be fully controlled-for in the analysis. For example, it is plausible that the imperfect coverage of information is more severe for SMEs and less severe for larger companies. Furthermore, the time-lag with which the information is observed may cause over-representation of older companies and of companies that did not undergo structural re-organizations post-2011 and instead under-represent young ventures and companies that underwent structural re-organizations.

Second, the identification strategy of companies that were affected vs. not-affected by counterfeiting in the firm-level database relies on the coverage and completeness of the OECD-EUIPO database (OECD, 2009; OECD-EUIPO, 2015). Specifically, firms were coded as counterfeit-targets by virtue of their being listed in the OECD-EUIPO database. By difference, the companies not listed in the OECD-EUIPO database were considered not targeted by counterfeiting and included in the control sample. Measuring counterfeiting is a particularly challenging task, due to the criminal nature of the activity (see box 3.1). The identification strategy adopted in this report shares all the strengths and weaknesses of the methodology employed in the OECD-EUIPO database (OECD, 2015) (Box 3.1). As a consequence, it is possible that the control sample includes companies that suffered from counterfeiting activities, which were not reported in the OECD-EUIPO for different reasons: the counterfeiting was not detected by the authorities; it related to non-physical goods (e.g. piracy of software, music, video occurred online); it related to goods produced and traded solely within the national borders; the companies were affected by counterfeiting activities before or after the window of observation; the counterfeiting happened in economies that were not covered by the OECD-EUIPO database.

Box 3.5 Measuring counterfeiting

Counterfeiting is an illegal activity. As a consequence, measuring counterfeiting is an inherently difficult task that poses considerable methodological problems. There are two families of approaches proposed: i) enforcement data (e.g. seizures) provided by national and international authorities, and ii) surveys of supply and demand.

Both methods have limitations. The largest limitation of the first method relates to mapping necessarily a small portion of the real counterfeiting activity. The largest limitation of the second relate to their self-reported nature. For example, consumers would likely report lower-than-real values, whereas companies may be reluctant to answer, due to the sensitive nature of the information.

The OECD-EUIPO is based on records of seizures of counterfeits goods detected by custom authorities in charge of the monitoring of international trade. As such, the data represent only the subset of all illegal trading potentially occurring, which was detected by the authorities. Furthermore, the detection is limited to: i) physical goods, ii) cross-border trade activities, iii) the time-period 2011-2013 and iv) the economies that cooperated voluntarily in the supply of data (OECD, 2009).

Despite its limitations, the OECD-EUIPO data is currently the largest, more comprehensive and reliable dataset for measuring counterfeiting at the global scale.

Finally, seizures are more likely to be operated on ground of violations of brands and trademarks, because violations of these types of IPRs are easier to detect by custom authorities compared to violations of patents and copyrights. As a result, the sample may be biased in favour of companies that use brands and trademarks more extensively, compared to patents.

These caveats will need to be kept in mind when using the data and interpreting the results of the analyses. They also suggest the importance of repeating the analysis with more data in the future for robustness and consolidation.

In conclusion, the firm-level database of digital technology companies affected by counterfeiting was constructed using a mix of content analysis, automatic matching and manual matching. The information it contains was sourced from four different databases. The data have limitations, due to partial coverage of several information. The limitations should be kept into account when interpreting the data and call for more analyses with enhanced databases in the future.

Despite the limitations, the firm-level database represents a unique and original source of data. Its strength stands on the firm-level structure and on its unique combination of information of counterfeits, economic performance and innovation performance. Compared to prior analyses, it provides unprecedented potential to investigate the characteristics and impact of counterfeiting activities at the firm level and on a global scale.

4 Digital companies affected by global trade of counterfeit goods

4.1 Counterfeiting affecting the digital technology companies

Digital technology companies affected by counterfeiting represent the 10.9% of the OECD-EUIPO database. In the period 2011-2013, these companies accounted for 38,767 seizures, corresponding to the 9.1% of the total number of seizures reported in the OECD-EUIPO database.

The total value of seized goods related to the digital technology companies amounts to USD 786 million, which corresponds to 9.1% of the total value of seized goods in all sectors (Table 2).

Table 2. Comparison between the final sample and OECD-EUIPO database

	Companies	% companies	Seizures	% seizures	Tot Value (USD)	% value
Digital	260	10.9%	38,767	9.1%	786m	9.1%
Non-digital	2,132	89.1%	388,612	90.9%	7,850m	90.9%
Total	2,392	100%	427,379	100%	8,636m	100%

Overall, the value of the seizures of counterfeits related to the digital technology companies increased in the considered time frame: from USD 0.24 bn in 2011, to USD 0.43 bn in 2013 (Table 3). Correspondingly, the unit value of the average seizure case increased from USD 17,063 in 2011 to USD 41,013 in 2013.

Table 3. Yearly value of seizures in bn USD

Year	Digital (BUSD)
2011	0.235
2012	0.119
2013	0.432

The distribution of the unit value of seizures is highly dispersed, ranging from seizures of very small amounts, to seizures of over a USD 1 million (Table 4). About 29.6% of companies in the period 2011-2013 were affected by seizures of small entity, with seized goods value estimated to be lower than USD 5,000. By contrast, more than 20% of the companies were affected by seizures with a total value equal or greater than USD 500,000 and 18.8% were affected by seizures valued between USD 100,000 and USD 500,000.

The seizures are 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. A rank-ordering of the companies by descending number of total seizures, indicates that the top four companies accounted for the 54% of total seizures; the top ten companies accounted for 80% and the top twenty companies accounted for 89%. At the same time, there are seventy-four companies included in the sample by virtue of only one seizure. This large disparity in concentration may reflect in part the circumstance that some companies are more heavily targeted by counterfeiters than others. However, it also reflects in part the larger effort placed by some companies in contrasting counterfeiting activities, compared to other companies. For this reason, it is important to consider all companies targeted, instead of focusing only on those with a greater incidence of seizures.

Table 4. Distribution of companies by classes of total seized good value in years 2011-2013

Value of the seized good	Number of companies	Perc.
0-5,000	77	29.6%
5,000-10,000	18	6.9%
10,000-50,000	42	16.2%
50,000-100,000	20	7.7%
100,000-500,000	49	18.8%
500,000-1,000,000	15	5.8%
>1,000,000	39	15.0%

4.2 Characteristics of companies affected by counterfeiting

4.2.1 Location

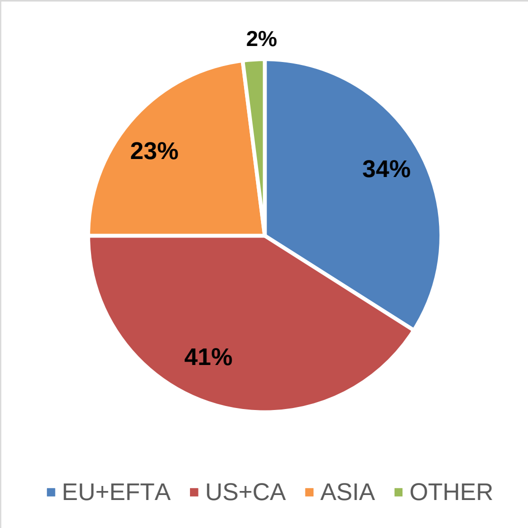
The 41% of digital technology companies affected by counterfeiting in the period 2011-2013 was located in North America (US and Canada), while 34% resided in either of the EU28 or EFTA countries and 23% in Asia (Figure 3, left panel). United Kingdom, Germany, France, and Italy were the countries hosting the largest number of European digital technology companies affected by counterfeiting, with about the 77% of the European digital technology companies located in these four countries.

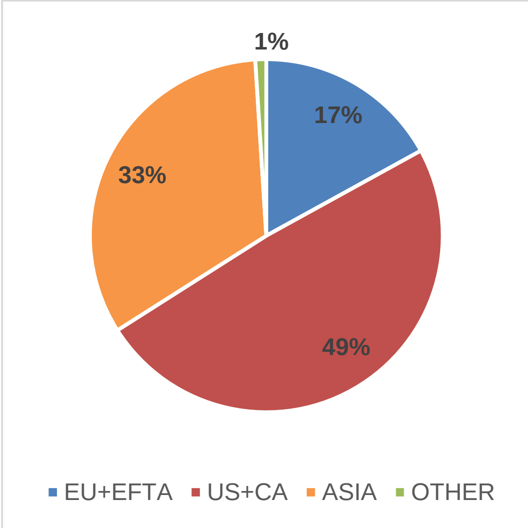
The European digital technology companies affected by counterfeiting accounted for 17% of the total seizures. By contrast, North America accounted for the 49% and Asia accounted for the 33% of the total seizures of digital technology companies, because of few very large companies located in Japan and Korea (Figure 3, right panel).

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%). About 3% of counterfeits seized came from Singapore. Other economies of provenance account for less than 1% of the seizures (Figure 4). China and Hong Kong, China were the most common departing points of counterfeit goods for 225 out of the 260 digital technology companies (86%).

By contrast, counterfeit goods coming from the EU28+EFTA countries represented a very limited share of the total seizures. Switzerland and Greece were the most common departing points of counterfeit digital goods in the EU28+EFTA area, respectively accounting for 0.2% and 0.1% of the total number of seizures related to products of digital technology companies.

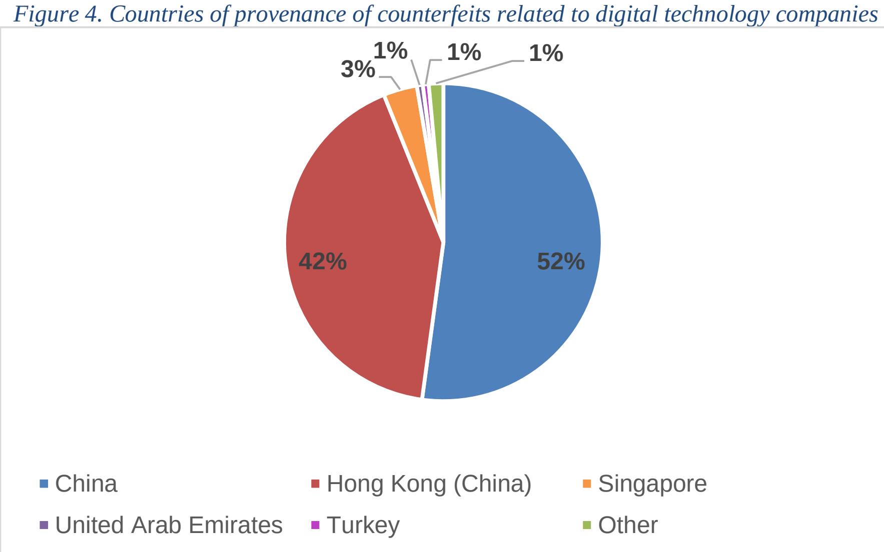
Figure 3. Geographical location of companies affected by counterfeiting by number of companies (left) and by number of seizures (right)





Within the EU28+EFTA, Germany and UK, followed by Belgium and Ireland, were the most common country of destination of seized counterfeits. However, a clarification is in order here. Destination country indicated in the OECD-EUIPO database is the last known destination point of the seized good, but not necessarily the final one. It is possible that these countries serve only as temporary destinations for counterfeit goods that are subsequently packaged and shipped to a different country. This advises caution, when interpreting the results.

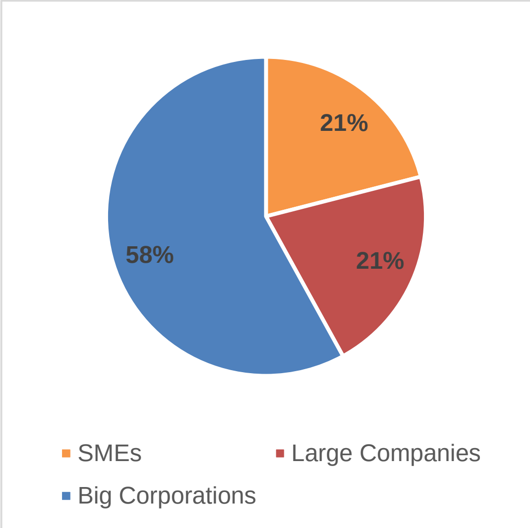
Figure 4. Countries of provenance of counterfeits related to digital technology companies



4.2.2 Company dimension

In terms of dimension, digital technology companies affected by counterfeiting in the period 2011-2013 were disproportionately representative of large or very large entities. The 58% of the digital technology companies affected by counterfeiting for which financial data are available were big corporations, identified as those having Operating Revenues greater than USD 1 bn (Figure 5). About 21% of the firms affected by counterfeiting were large companies, identified as those having Operating Revenues smaller or equal to USD 1 bn, but greater than USD 50 million. Similarly, the 21% of digital technology companies affected by counterfeits were SMEs, identified as those having Operating Revenues smaller or equal to USD 50 million.

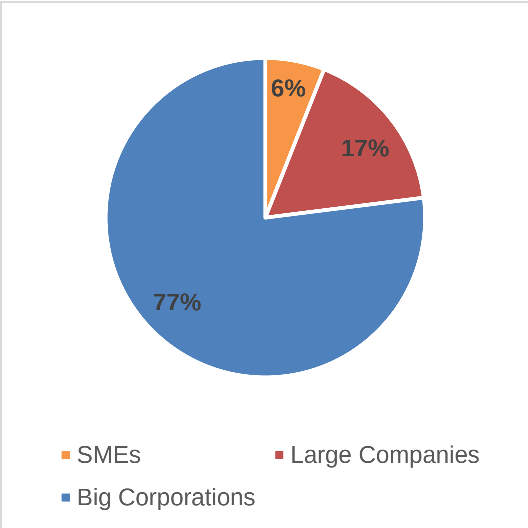
Figure 5. Dimension of digital technology companies affected by counterfeiting

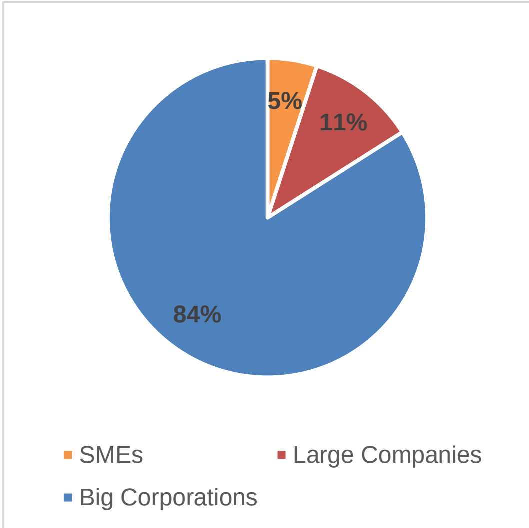


Overall, the distribution suggests that, although counterfeiting activities can potentially affect all digital technology companies, big corporations are disproportionately targeted. This result is in part expected and depends on the circumstance that counterfeiting targets specifically valuable brands, which in turn are likely to be owned by large corporations (Berger et al. 2012). However, recalling the caveats highlighted in section 3.5.1, it is important to stress that the SMEs could have been under-represented in the sample considered due to imperfect coverage in the databases of origin of economic and financial information.

Big corporations account for 84% of all the seizures related to digital technology companies (Figure 6, left panel) and for 77% of the total value of seizures (Figure 6, right panel). By contrast, SMEs represent only the 5% of the seizures related to digital technology companies and account for 6% of the total value of seizures. Again, it is important to stress that the SMEs could have been under-represented in the final sample, due to imperfect coverage.

Figure 6. Seizures value by company size (left) and seizures count by company size (right)





4.2.3 Industry

NACE codes provide insight on the sectoral distribution of digital technology companies. The 31% of the digital technology companies affected by counterfeiting in the period 2011-2013 were manufacturers of computers, electronics, and optical equipment (Table 5). 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 4-digit NACE, followed by manufacturers of computers and peripheral equipment and consumers' 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, mobile phones components), and to consumers' market (e.g. computer's 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. Automotive manufacturers are also the group of companies affected by counterfeits that are relatively more sizable in the EU28+EFTA countries (18% of European digital companies). Counterfeit goods in this sample are primarily aimed at a business market. Examples of counterfeit goods seized related to automotive companies include digital commands wheels and digital control units.

A third group of companies affected are media corporations. Collectively, these represent 8.8% of digital technology companies affected by counterfeiting in the period 2011-2013 and account for 3.8% of total seizures. Counterfeit goods in this sample are primarily aimed at a consumer's market. Examples of counterfeit goods seized related to media corporations include CDs and DVDs. Other categories of companies represented in the sample are producers of toys with digital components, and producers of digital music equipment and instruments.

Table 5. Distribution of digital technology companies affected by counterfeiting*

NACE code	Description	Frequency	Percent
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 programme 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	

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

4.3 Patenting activities of companies affected by counterfeiting

The analysis of the type of IPR infringement reveals that the most likely violations of IPRs of digital technology companies is represented by trademarks, followed by design and model rights. However, recalling section 3.5.1, this result may be due, at least in part, to the fact that the infringement of trademarks and brands is easier to detect by custom authorities, compared to that of patents is more difficult to be detected.

Trademarks represents 92.8% of the total number of seizures and 94.5% of the total seized value (Table 6). When considering the average value of the seizures, trademark violations are worth USD 20,655, less than half of the value of seizures associated to patent violations (USD 53,567). This indicates that, on average, seizures due to violations of patents tend to be larger in magnitude compared to those related to trademarks.

Table 6. Type of IPR infringements in the examined dataset

Type of IPR infringement	% of seizures	Seizures value (M USD)	Mean seizure value (USD)
Trademark	92.8%	743	20,655
Design and Model right	4.5%	22.4	12,771
Copyright	2.1%	9.5	11,554
Patent	0.4%	8.7	53,567
Protected Geog. Ind.	0.1%	2.2	62,238
N/A	0.1%	0.01	675
Total	100.0%	786	20,275

Based on the searches of patent repositories described in section 3.3, the patent portfolios of the digital technology companies with priority year between 2009 and 2015 were identified. In total, the search resulted in 843 thousand patent families.[10] For 185 of the digital technology companies affected by counterfeits (71%), at least one patent application in the period of observation was identified, suggesting considerable R&D intensity. The remaining 75 digital technology companies (29%) resulted to have filed no patent applications.

The average digital technology company in the sample filed about 3,243 applications in the time interval, but the distribution is very skewed. Table 7 displays the distribution of the digital technology companies affected by counterfeits by portfolio size. 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 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 about 50% of the patent families in the examined sample, while the companies with the 30 largest portfolios account for 82% of total patent families. Patent holders with less than 1,000 families represent 42% of the sample; 29% of companies have filed applications for more than 1,000 patent families.

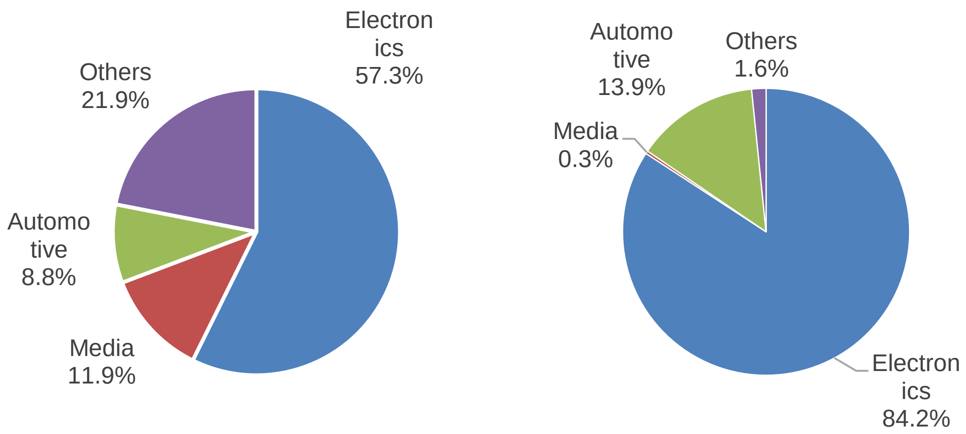
Table 7 Distribution of firms in the sample in terms of portfolio size, measured as number of patent families, and median value in each group

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 1,000	14	5%	716
From 1,001 to 2,500	25	10%	1,726
From 2,501 to 5,000	14	5%	3,345.5
From 5,001 to 1,0000	12	5%	7,762
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**

[10] A single patent family represents the bundle of all patent applications stemming from a specific original innovation. Using patent families allows avoiding double/counting.

Figure 7 reports a sectoral breakdown of the digital technology companies by number (left panel) and by patent families (right panel). The largest share of patent families (84.2%) is owned by electronics companies (57.3%); automotive companies (8.8%) own about the 13.9% of patent families, while media corporations (11.9%) account for only 31 patent families, corresponding to 0.3% of the total patent families.

Figure 7 Distribution of companies (left) and of patent families (right) across the main macro industries in the sample



5 Characteristics of companies affected by counterfeiting

This section aims at identifying the risk factors that make a digital technology company more likely to be a target of counterfeiting.

Whereas in section 4 we looked separately at the characteristics of digital technology companies, like size, profitability, sector and country, the methodology used in this section accounts jointly for all the different characteristics of firms in comparison with those of a control sample of companies not targeted by counterfeiting.

5.1 Methodology: Analysing the likelihood of counterfeit

In order to investigate the firm-level factors that are associated to the likelihood of being subject to counterfeit we use an econometric approach based on Logit models. In Logit models the dependent variable is dichotomous, taking the value of one for the firms affected by at least one counterfeiting case during years 2011-2013 and zero for those that were not affected. The not affected firms (control sample) is the one described in the section 3.3.

The general model specification is the following:

$$Pr(Counterfeited=1)=F(b_o+ b_1*SIZE + b_2*GROWTH + b_3*ROA + b_4*INTANG +$$

$$+ b_i *SECTOR\ DUM + b_j*COUNTRY\ DUM) \qquad Eq.\ (1)$$

where F is the cumulative logistic function, “b” are coefficients to be estimated, b_i is a vector of coefficients for the sectors, b_j is a vector of coefficients for economies. A positive estimated coefficient for a parameter b in the above equation implies an average positive impact of the related variable on the likelihood of a company being subject to counterfeit.

The explanatory variables used in the models include:

- Company size (variable SIZE), computed as the log of the Operating Revenues. In some model specifications the single continuous variable SIZE is replaced by a set of dummy variables identifying the company firm class (BIG: equals one for companies with a turnover above USD 1 bn; LARGE: equals one for companies with a turnover between USD 50 million and USD 1 bn; SMEs: equals one for companies with a turnover equal or below USD 50 million).
- Firm profitability, measured by the Return On Assets (ROA), i.e. the ratio of Earning Before Interest and Taxes (EBIT) to Total Fixed Assets.
- The amount of Intangible Assets (INTANG);
- The growth rate of the business (GROWTH), measured as the growth rate of sales over a 2-years time period before the window of observation of counterfeits
- Sector dummy variables defined at NACE 2-digit level
- Country dummies based on the country of incorporation the company

In order to limit the incidence of potential 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.

Sector dummies are used in order to control for the potential differences in the likelihood of infringement across different industries. This variable is operationalised using 2-digits NACE codes. All models include a set of country dummies, identified as the country of incorporation of the company.[11]

It is important to stress that in this analysis the likelihood to be affected by counterfeit was modelled, irrespective of the relative intensity of the infringement (i.e. the total number of seizures or the total value of seized goods). Recalling the caveats discussed in section 3.5.1, the values of the seizures may in fact under-represented the real entity of the counterfeit value in place, because it is plausible to presume that not all counterfeited goods are detected at the custom. Furthermore, it is possible that the intensity of counterfeits is also affected by the anti-counterfeit activities of companies (Wilson and Sullivan, 2016). By using a single dummy for the presence or absence of counterfeiting activity, the analysis refrains from making assumptions on the unknown entity of the counterfeiting in place. Instead, the presence of at least one seizure in the time interval indicates that a counterfeit activity of any size is in place.

5.2 Results: Factors affecting the likelihood of being targeted by counterfeiting

Table 8 reports the results on the set of Logit model estimates on the likelihood of being affected by counterfeiting. The model is applied on a dataset that includes both digital firms subject to counterfeiting and a large control sample of firms not infringed. The control sample used is the one described in section 3.3.

All models indicate a positive and highly significant correlation between the company size and the likelihood of being affected by counterfeit. This evidence holds both when using a continuous indicator of firms' size (Model I) or when adopting industry size classes (Models II - IV). This positive correlation is also robust to the inclusion of both sector and country dummies.

Interestingly, in all models a positive and significant correlation between the firm-level endowment of Intangible Assets (variable INTANG) and the likelihood of being infringed is observed.

The performance of the firm in year 2010, measured by the return on Fixed Assets (ROA) shows a weak but positive correlation with the likelihood of being affected by counterfeiting activity across all the different model specifications, suggesting that companies performing at a higher level prior to the window of observation were more likely to be targeted by counterfeiting. This result is consistent with prior studies based on survey data (Berger et al., 2012).

The growth rate of the Operating Revenues (variable 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. This suggests that companies that were targeted by counterfeiting activities had a lower-than-average growth of sales in the years before the window of observation. Such 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.

[11] Note that this may not correspond to the country in which the counterfeit seizure occurred.

Table 8. Logit models. Dependent variable: likelihood of being affected by counterfeit during years 2011-2013. Covariates set at year 2010. Sample including non-infringed control firms. Omitted category for the size dummies: SME.

MODEL	I	II	III	IV
OUTCOME	**AFFECTED BY COUNTERFEITING**	**AFFECTED BY COUNTERFEITING**	**AFFECTED BY COUNTERFEITING**	**AFFECTED BY COUNTERFEITING**
SIZE	0.8241***	0.8763***		
	(0.086)	(0.092)		
BIG			4.5706***	4.2854***
			(0.707)	(0.581)
LARGE			2.3323***	2.2541***
			(0.695)	(0.580)
ROA	0.8137	1.3962*	1.4766**	0.5830
	(0.828)	(0.789)	(0.695)	(0.375)
GROWTH		-1.2657**	-0.8999*	-0.7691**
		(0.542)	(0.483)	(0.376)
INTANG	0.0541*	0.0521*	0.1625***	0.1849***
	(0.029)	(0.028)	(0.038)	(0.038)
EU Countries				-1.2855***
				(0.270)
Country dummies	YES	YES	YES	
Sector dummies	YES	YES	YES	YES
Constant	-10.7153***	-10.8587***	-3.0717***	-3.6586***
	(1.203)	(1.266)	(0.820)	(0.631)
Observations	5,538	4,919	4,919	4,919
Chi-Sq	452.9***	449.8***	362.2***	431.6***
Log-Likelihood	-229.5	-208.3	-224.9	-279.9
pseudoR2	0.497	0.519	0.446	0.435

*p<.1; **p<.05; ***p<.01

Model IV adopts a single dummy variable (EU countries) that takes the value of 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 infringement compared to 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 EU28 appears to be relatively less affected by counterfeiting activities than digital technology companies located elsewhere. This effect is present after controlling for sector and size of the firms, hence net of potential structural differences between EU and non-EU based firms.

The joint analysis of the different firm-level characteristics indicates that, net of sector specific effects, firms subject to counterfeit are on average of large size, with larger endowment of Intangible Assets, a profitability slightly larger than the control sample and lower growth rate of Operating Revenues in the years before the window of observation of the counterfeiting cases. Moreover, companies incorporated in EU countries show, net of all previous factors, show a relatively lower propensity to being subject to counterfeiting compared to companies located elsewhere.

6 Impact of counterfeiting on the economic performance of digital technology companies

This section presents the evidence concerning the impact of counterfeiting activities on the economic performance of digital technology companies. The assessment of the economic impact of counterfeiting is a complex task for a number of methodological issues. Section 6.1 discusses these issues and presents the different methodologies that have been adopted in order to overcome these issues and estimate the impact of counterfeit on economic performance of the digital technology companies. Results of the econometric models are presented in section 6.2.

6.1 Methodology: assessing the firm-level impact of counterfeiting

The estimation of the impact of counterfeiting on the subsequent performance of firms is a challenging task for two main sets of factors: the need to disentangle the trends in performance that can be attributed to the counterfeiting activity; the partial observability of the counterfeiting phenomenon. The use of appropriate data modelling techniques that are commonly used in impact analysis (e.g. for the estimation of the effects of public policy or for the validation of medical treatments) can address the former factor. In particular the use of well-defined control samples can allow to control for the fact that during the observed years there might be sector-level factors that influence the economic performance of the firms and are indeed unrelated to the counterfeiting.

However, the peculiar nature of the counterfeiting poses specific issues that can be only partly addressed.

In particular, the actual magnitude of the counterfeiting is unknown, due to the nature of the data, which likely represent only a subset of the actual products illegally traded. The presence of repeated seizures along the observed years for a specific company makes it difficult to identify a time period *before* and *after* the counterfeiting in the estimation of an impact. Moreover, there might be a time lag between the moment of the seizure and the moment when the counterfeiting actually started.

Furthermore, it is important to stress that firm performance is potentially endogenous to counterfeiting, because of the circumstance that counterfeiters target high-performing products and profitable brands (Berger et al., 2012). This in turn might lead to the estimation of a biased positive correlations between counterfeiting and performance, especially when dealing with datasets that are necessarily limited in time.

In addition to the above methodological caveats, it has to be recalled that the firms included in the sample belong to different industries. This introduces a significant source of heterogeneity in all the econometric models, which necessarily estimate an average impact.[12]

Taking into consideration all the above important caveats, and the nature and coverage of available data, different analyses were conducted with the purpose to mitigate at least in part the problems highlighted. Specifically, the analysis employs control samples, matching pairs methods, treatment effects, difference-in-difference and instrumental variables estimates for different groups and years of observation.

Multiple outcome variables were used to capture different dimensions of performance. Specifically, the outcome variables used to measure the economic performance are: Operating revenues (sales), two different measures of Operating Profits, i.e. the Earning Before Interest, Taxes, Depreciation and Amortization (EBIT), the Earning Before Interest and Taxes (EBIT), the Return on total assets (ROA) and the investments in Fixed Assets.

[12] The number of firms subject to counterfeiting is relatively too small to conduct econometric analyses within industry groups.

6.1.1 Difference in difference method

Difference-in-difference is a statistical technique meant to compare a specific outcome variable across a treated sample (companies affected by counterfeiting activities) and a control sample (companies not affected by counterfeiting activities), before and after the treatment. In particular, it estimates the effect of a treatment on an outcome variable by comparing the average change over time in the outcome variable for the treatment group, compared to the average change over time for the control group.

The comparison with the control sample over time enables to discount the change in the outcome variable that has occurred because of reasons other than the counterfeiting (e.g. the average industry trends) during the relevant years. The comparison of a treated company over time enables to discount the difference in the magnitude of the outcome variable that is specific to the treatment group. Hence, the estimation technique is intended to mitigate the effects of both extraneous factors (e.g. trends) and selection biases (e.g. the affected companies are among the best-performing).

The general specification for a difference in difference model is the following:

$$Y_{i,t} = a + b^*T_{i,t} + c^*t_{i,t} + d^*\ T_{i,t} * t_{i,t} + e_{i,t} \qquad \text{Eq (2)}$$

The specific definition of the parameters to be estimated (a, b, c, d) and variables in the previous equation is the following:

$Y_{i,t}$ is the outcome variable of firm *i in period t*

$e_{i,t}$ is an error term.

T: treatment variable (1 for treated; 0 for non treated)

t: period variable (1 for the period after treatment; 0 for the period before treatment)

a = constant term

b = treatment group specific effect (to account for average permanent differences between treatment and control groups)

c = time effect common to treatment and control groups

d = true effect of treatment

In particular, the parameter (d) captures the difference among the sub-groups before and after the treatment, hence depurating it from the effects of common trends.

In the specific setting of this study the model specification entails that:

$T_{i,t}$ = 1 for firms with at least one counterfeiting event during years 2011-2013

$T_{i,t}$ = 0 for firms with no counterfeiting events during years 2011-2013

$t_{i,t}$ = 0 in pre-treatment period. Note that the year 2010 or the time window (2008-2010) were used in alternative model specifications.

$t_{i,t}$ = 1 in post treatment period. Note that the year 2014 or the time window (2011-2014) were used in alternative model specifications.

6.1.2 Propensity score matching method

A second methodology that can be adopted to investigate the impact of counterfeit is the Propensity Score Matching (PSM) (Caliendo and Kopeinig, 2008). This method implies that each company affected by counterfeiting is paired with one or more companies that are similar in terms of risk to be infringed, but have not been affected by counterfeiting. The objective is to improve the capability to isolate the specific impact of counterfeiting by discounting the changes in the variables that have occurred to the paired companies and are therefore presumably unrelated to counterfeiting.

In terms of operations, the methodology entails three steps. First, it computes a company-specific risk factor to be affected by counterfeit (propensity score) for each company in the treated and control group. This is based by running a selection equation that replicates the Logit model of Eq. 1 on pre-treatment data, i.e. for the year 2010. Second, each affected company is paired with the 5 companies that have the greatest similarity in the risk to be affected. The 5 are selected with the nearest-neighbour method from the broadest control sample, with replacement, i.e. each company in the control sample can be paired to more than one treated firm. The large size of the control sample enabled applying a rather conservative tolerance threshold for the similarity in the risk factor, equivalent to a maximum caliper of 0.05 (Cochran and Rubin, 1973). Third, the analysis is based on comparing the paired differences across the two samples in the ex-post growth rates of various outcome variables.[13] In particular, the models report the Average Treatment Effect, i.e. the difference in the outcome variable between the paired samples of treated and control firms.

6.1.3 OLS and Instrumental Variables method

The diff-in-diff and PSM methodologies adopted to analyse the impact of counterfeit and illustrated in the previous sections are based on an on/off measure of counterfeiting, which indicates whether or not the company experienced at least one counterfeit event during the years 2011-2013. They do not take into account the differences that may exist across companies concerning the number of seizures experienced during the time window. To consider this additional information, a set of additional panel models is performed, in which an yearly outcome variable for both the treated firms and the broad control sample is predicted by an indicator of the intensity of the counterfeiting activity (number of seizures in a given year) a set of firm-level controls.

These models comprise the simple Ordinary Least Square (OLS), as well as Instrumental Variables regressions (IV-reg). It is important to note that the Ordinary Least Square models are potentially affected by endogeneity, due to positive selection into treatment discussed in section 4.2, i.e. the circumstance that firms affected by counterfeiting are among those having larger turnovers. The Instrumental Variable regression was adopted in order to partly mitigate this problem. In the IV-reg the endogenous annual number of seizures is instrumented by means of the two-years lagged level of sales and profitability. The IV-reg model that results estimates whether - net of the firm size effect - the intensity of the counterfeiting phenomenon (measured by the number of seizures), explains differences in the economic performance of the companies.

6.2 Results of diff-in-diff models

This section reports the results for a set of diff-in-diff models that estimates the impact of counterfeiting activity on different measures of economic performance: Operating Revenues, Operating Profits, expressed by Earning Before Interest Depreciation Amortisation and Taxes (EBITDA), and Earnings Before Interests and Taxes (EBIT), and investments in Tangible Assets.

Table 9 reports the results for Operating Revenues and different time intervals for the pre and post treatment periods. The results indicate that the treated group (firms affected by counterfeits) shows on average a larger volume of Operating Revenues compared to the control group (firms not affected by counterfeits), both before and after the treatment [Diff t(0) and Diff t(1)]. This is consistent with the evidence that larger firms are more likely to be targeted. However, the difference of such differences [Diff-in-diff] takes a negative sign, implying that the

[13] All PSM models have been performed with the routine teffects-psm of the econometric software STATA 14.

superior performance (higher Operating Revenues) of the treated group compared to the non-treated group before the counterfeiting was still existing after the treatment, but had shrunken. In other words, affected companies experienced a relative lower positive trend of sales with respect to the control sample of non-affected companies. However, this evidence is subject to high standard errors. It is not statistically significant in Model I, whose specification is reported in Eq.2, and Model II, whose specification includes sector and country dummies. It is statistically significant at 95% confidence interval in Model III, when a longer window of observations is adopted.

In conclusion, the overall evidence points at a negative, but only weakly significant average impact of counterfeiting on Operating Revenues.

Table 9. Difference in difference models. Dependent variable: sales. Treatment variable: infringement during years 2011-2013. Multiple time interval.

MODEL	I	II	III
OUTCOME	**OPER. REVENUES**	**OPER. REVENUES**	**OPER. REVENUES**
Time	T_0: 2010 T_1: 2014	T_0: 2010 T_1: 2014	T_0: 2009-2010 T_1: 2011-2014
Diff-in-diff	-126.94	-51.78	-94.85**
Std err	(79.187)	(75.161)	(45.792)
Sector and country dummies	NO	Yes	No
Observations	35,585	35,585	109,609
R-squared	0.1230	0.2194	0.1240
Diff t(0)	2856	2622	2856
Diff t(1)	2729	2570	2761

**p<.05

Table 10 reports the results for a similar model, where the outcome variable is an Operating Profit, i.e. the EBITDA. This is a performance measure that takes into account not only the differentials in sales, but also the differentials in operating costs between the treated and the control firms. In this case, it is observed a clear and robust indication of a negative association between the treatment (i.e. being infringed) and the dynamics in time of the EBITDA of the treated firms compared to the control sample.

Table 10. Difference in difference models. Dependent variable: EBITDA. Treatment variable: infringement during years 2011-2013. Multiple time interval.

MODEL	I	II	III
OUTCOME	**EBITDA**	**EBITDA**	**EBITDA**
Time	T_0: 2010 T_1: 2014	T_0: 2010 T_1: 2014	T_0: 2009-2010 T_1: 2011-2014
Diff-in-diff	**-49.981*** **	**-48.846*** **	**-12.520***
Std err	(13.897)	(13.011)	(7.580)

Sector and country dummies	NO	Yes	No
Observations	28,327	28,327	93,493
R-squared	0.1940	0.2966	0.191
Diff t(0)	598	545.7	563.2
Diff t(1)	548	496.9	550.7

*p<.1; ***p<.01

Table 11 replicates the analysis, for robustness purposes, by taking an alternative measure of Operating Profit, the EBIT (i.e. the EBITDA, net of depreciation and amortization), as the performance indicator. The results are robust and consistent with the estimates of Table 10, irrespective of the model specifications adopted.

Table 11. Difference in difference models. Dependent variable: EBIT. Treatment variable: infringement during years 2011-2013. Multiple time interval.

MODEL	I	II	III
OUTCOME	**EBIT**	**EBIT**	**EBIT**
Time	T_0: 2010 T_1: 2014	T_0: 2010 T_1: 2014	T_0: 2009-2010 T_1: 2011-2014
Diff-in-diff	**-39.517*** **	**-34.525*** **	**-11.129*** **
Std err	(6.032)	(5.784)	(3.273)
Sector and country dummies	NO	Yes	No
Observations	36,007	36,007	117,381
R-squared	0.0933	0.1766	0.0816
Diff t(0)	202.5	187.5	170.9
Diff t(1)	163	153	159.7

***p<.01

Table 12 employs total Fixed Assets as the outcome variables. In this case, a clear impact (either positive or negative) is not observable. The treated and the control firms do not show a statistically significant difference in their investment in Fixed Assets and it is therefore impossible to derive a conclusive evidence on the impact of the infringement on the investment in Fixed Assets.

Table 12. Difference in difference models. Dependent variable: Total Fixed Assets. Treatment variable: infringement during years 2011-2013. Multiple time interval.

MODEL	I	II	III
OUTCOME	**TOT ASSETS**	**TOT ASSETS**	**TOT ASSETS**
Time	T_0: 2010 T_1: 2014	T_0: 2010 T_1: 2014	T_0: 2009-2010 T_1: 2011-2014
Diff-in-diff	**-160.0459**	**-58.9329**	**-63.4698**
Std err	(102.051)	(96.339)	(56.311)
Sector and country dummies	NO	Yes	No
Observations	46,297	46,297	150,925
R-squared	0.1207	0.2258	0.1241
Diff t(0)	4146	3822	4090
Diff t(1)	3986	3763	4027

Note that in the diff-in-diff analyses pool together firms operating in different subfields of the digital technology spectrum (e.g. Electronics, to Automotive, Media et cetera), which are presumably characterised by very heterogeneous price elasticities. The diff-in-diff models include controls for average sectoral effects, which can only partly capture this heterogeneity. The lack of straightforward conclusions concerning the relative dynamics of sales and profit margins can be in partly due to this limitation. However, the identification of an average negative and significant impact on EBIT and EBITDA is robust and significant and seems to point at a clear negative impact of counterfeiting activities on the Operating Profits of digital technology companies.

6.3 Results of propensity score matching models

This section presents the results on the impact of counterfeiting using the PSM techniques. Specifically, the models analyse the following measures of economic performance over the period 2011-2015:

i) Growth rate of the Operating Revenues

ii) Growth rate of Earning Before Interest Taxes Depreciation and Amortization (EBITDA)

iii) Growth rate of Earning Before Interest and Taxes (EBIT)

iv) Growth rate of Total Assets

v) Level of Return on total assets (ROA) in 2015

Table 13 reports the Average Treatment Effects (ATE) using the PSM model for the different outcome variables. The estimates point at a significant negative treatment effect of counterfeiting on the growth rate of Operating Profits (EBITDA, Model II or EBIT, Model III). This is consistent to the evidence provided by the diff-in-diff models.

Conversely, there is no evidence of a statistically significant impact of counterfeiting on the growth of Operating Revenues (Model I) or total assets (Models III and IV). The comparison with matching-paired sample also confirms a non-significant impact on the profitability, as expressed by the return on total assets (Model V).

Table 13. Propensity Score Matching Average Treatment Effects. Models based on 5 nearest matches. Different outcomes variables.

Models	I	II	III	IV	V
Outcome Variable	**Growth rate of Oper. Rev. (2011-2015)**	**Growth rate of EBITDA (2011-2015)**	**Growth rate of EBIT (2011-2015)**	**Growth rate of Total Assets (2011-2015)**	**Profitability in year 2015 (ROA)**
Average Treatment Effect: (Infringed vs. Non Infringed)	0.1755	-0.2043**	- 0.575*	0.1580	0.0779
Std. Err	(0.166)	(0.103)	(0.339)	(0.119)	(0.105)
P-value	0.289	0.048	0.089	0.184	0.456
Observations	5,348	4,122	3,783	5,429	5,184

**p<.05; *p<.1

6.4 Results of OLS and Instrumental variables models

This section presents the results of analyses based on panel data, covering the years 2011-2013 for the full sample of companies that were affected and not affected by counterfeiting. In line with the results of the models presented in section 6.2 and 6.3, the dependent outcome variables are the annual Operating Profits, expressed by EBITDA and EBIT. The explanatory variable is the count of seizures in a given year and the control variables include the yearly financial data and the time-invariant dummies for country and sector.

Model I of Table 14 reports the results of an OLS random effects estimate. The result confirm that the EBITDA is negatively correlated to the number of seizures experienced by companies. The result is statistically significant at a 95% confidence interval.

The latter evidence might be affected by endogeneity, due to positive selection into treatment, i.e. the circumstance that firms with larger turnovers have greater likelihood of being affected by counterfeiting. In order to partly mitigate this problem, an Instrumental Variable regression (IV-reg) model was adopted, in which the annual number of seizures is instrumented by means of the two-years lagged level of sales and profitability. The results of the IV-reg are reported in Model II of Table 14. The results corroborate the evidence of a negative correlation between the number of seizures experienced and the EBITDA of the companies during the years of observation at a 95% confidence interval. Note that all effects are robust to the inclusion of country, sector and year dummies. Overall, the results of OLS and IV models are in line with the those of the PSM and diff-in-diff models presented in previous sections.

The models II and IV of Table 14 report the estimates of the OLS model and the IV-reg models using as the outcome variable the EBIT, instead of the EBITDA. All results are confirmed.

Table 14. Panel models on number of seizure and economic performance. Dependent variable EBITDA. OLS (I, III) and IV-reg models (II, IV)

MODEL	I	II	III	IV
OUTCOME	**EBITDA**	**EBITDA**	**EBIT**	**EBIT**
SEIZURES	-0.0253** (0.010)	-3.4873** (1.472)	-0.0688*** (0.007)	-6.1235*** (2.014)
SALES	0.0560*** (0.001)	0.0413*** (0.002)	0.0259*** (0.000)	0.0253*** (0.003)
TOT ASSETS	0.0572*** (0.001)	0.0813*** (0.006)	0.0189*** (0.000)	0.0442*** (0.008)
INTANG ASSETS	0.1750*** (0.005)	0.2013*** (0.019)	0.0598*** (0.003)	0.0298 (0.026)
Country dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	10.8098*** (4.058)	-27.3916** (13.822)	10.6179*** (2.263)	-36.9913* (19.350)
Observations	35,476	25,142	42,792	25,566
Number of id	15,170	11,833	18,229	12,014
R-Sq overall	0.829	0.580	0.643	0.119

**p<.05; ***p<.01

In conclusion, the results of both the diff in diff models and the propensity score matching suggest the presence of a negative but weakly significant impact of counterfeiting on the volume of sales, indicating that companies affected by counterfeiting may have experienced a slower growth in sales compared to those not affected by counterfeiting. However, this evidence is not always robust to the choice of model specification and is subject to a potentially large statistical error, calling for more analyses on new data in the future.

Instead, the results of the diff in diff, the propensity score matching, the OLS and the instrumental variables models are all coherently suggesting the presence of a robust and statistically significant negative impact of counterfeiting on the Operating Margins, both expressed in terms of EBITDA and EBIT. This indicates that companies affected by counterfeiting have experienced lower Operating Profits compared to companies not affected by counterfeiting. There is no evidence of an effect of counterfeiting on investment in Fixed Assets.

7 Impact of counterfeiting on the innovation performance of digital technology companies

This section addresses the impact of counterfeiting activities on the innovation performance of digital technology companies. Measuring innovative performance is an inherently difficult task which poses a series of methodological problems (Box 7.1). The analyses presented in this report are based on two measures of innovative performance: i) number new patents fillings and ii) investment in Intangible Assets. This methodological choice is partly motivated by the lack of consistent data on firm-level expenditures in R&D.

Box 7.1 Measuring innovation

There are two families of indicators commonly employed to measure innovation activities: amount of resources associated to R&D and patent data. A comprehensive analysis of the measures of innovation is available in two OECD publications (OECD, 1997 and 2009).

R&D data can be collected through surveys or from accounting information. The latter include R&D expenditures from the Income statement and intangible assets from the Financial Statement. The accounting procedures may differ across countries. However, the former is usually a measure of annual costs incurred for R&D, training, software, and other similar items and the latter relates to capitalized expenditures on IPRs (eg. patents, trademarks, etc.). This type of data has three main limitations: i) it is an input measure, not necessarily associated to a corresponding output; ii) R&D measures do not typically include learning-by-doing or other means that lead to technological advances; iii) they are difficult to collect and measures may vary across economies and over time.

Patent data filed or assigned to a company are a second measure of the output of innovation activities (Griliches, 1990). Patents are assigned by national patent offices and are recorded in open-access electronic databases, which can be accessed to elaborate statistics along several dimensions (time, technological classification, geographical scope, technical merit of the inventions, etc.). Patent-based measure of innovation also have limitations: i) innovations are not always patented, and may instead be kept secret, may be covered by other IP protection rights or not be protected; ii) the distribution of the economic value of patents is highly skewed, with a small fraction of patent having high commercial value and the majority of patents having a small value; iii) patents may be filed by firms for strategic reasons, e.g. to block competitors or create "patent fences"; iv) there are different industry-propensities to patent and patent law changed over time.

Other measures of innovation have been used by scholars to complement the previous two families include: number of R&D personnel, number of trademarks deposited, number of publications in scientific literature, the technology balance of payments, the level of activity in high-tech sectors (e.g. investments, employment, external trade), and the generation and/or adoption of information technology.

7.1 Methodology: assessing the impact of counterfeit on innovation performance

The study uses two outcome variables of innovation performance of companies: the annual number of new patent family filings and the Intangible Assets.

Concerning patenting activity, the study compares the innovation performance of companies (number of new patent family filings) that were affected by counterfeiting against the performance of a paired sample of companies that were not affected by counterfeiting. The paired sample was constructed by applying a PSM strategy, using a one-to-one nearest-neighbour matching with replacement, with a maximum caliper of 0.05. The selection model for the PSM was run on pre-treatment data (year=2010). In addition to the PSM method the study also included a paired one-to-one comparison *between* the digital companies and the corresponding matched firms, by looking only at the patent portfolios before (2009-2010) and after (2014-2015) the window of observation. For normally distributed paired differences, the T-test was performed under the null hypothesis of zero mean difference of the variable. When the distribution of paired differences was non-normal, the test was based on comparing if the variables in the two samples have a similar distribution by means of a Kolmogorov–Smirnov test.[14]

Concerning the investment in Intangible Assets the study adopts both the diff in diff and the PSM methods illustrated in Section 6.1.1 and Section 6.1.2.

7.2 Impact on patenting activity

Table 15 reports the comparison in patent filings *between* the digital companies and the corresponding matched companies (Columns I and II of Table 15) as well as the difference *within* each subsample before and after the period in which counterfeiting is observed (Columns III and IV of Table 15).
The analysis shows that, before the window of observation (years 2009-2010), the companies affected by counterfeiting have filed a significantly higher number of patents than the companies not affected by counterfeiting (Column I of Table 15). The same test, performed after the window of observation (Column II of Table 15), i.e. in years 2014-2015 indicates that the samples still have a significant difference in means. However, Columns III of Table 15 indicates that, on average, the number of patents filed by companies targeted by counterfeits decreased after the counterfeiting period, whereas the number of patents filed by companies not targeted by counterfeits remained overall unchanged over time (Column IV of Table 15).

The implications of counterfeiting activities on the invention performance of digital technology companies was further investigated, using a difference-in-difference model that includes sector and country controls. Table 16 reports the results of the estimates of the diff-in-diff models performed for different time windows.

The average effect is negative, suggesting a relative reduction in the difference between patent applications of the treated and control groups after the treatment. However, the standard errors associated to the diff-in-diff parameters is very high and the result is not statistically significant.

[14] Normality is evaluated with the Shapiro–Wilk test.

Table 15. Average patenting performance of companies that were affected V. not affected by counterfeiting. Between and within estimates

	Between groups (Diff: affected - not-affected)		Within groups (Diff: 2014-2015 – 2009-2010)	
	I Before (2009-2010)	II After (2014-2015)	III Affected by counterfeiting	IV Not affected by counterfeiting
Average difference	1,097.1	849.5	-247.5	12.5
(St. error)	(222.5)***	(188.5)***	(109.4)**	25.3

**p<.05; ***p<.01

The results, although suggesting a negative effect, do not provide a statistically robust evidence about the existence of a negative impact of counterfeiting on the investments of digital technology companies in innovation, as captured by patent filings. However, it is important to stress that this might be due in part by the relatively small sample and by considerable heterogeneity of the companies in the treated sample concerning the use and intensity of patents for protecting innovations.

Table 16. Difference in difference model. Treatment variable: at least one infringement. Multiple time interval. Sample based on PSM one-to-one nearest-neighbour match.

MODEL	I	II
OUTCOME	**PATENT**	**PATENT**
Time	T_0: 2009-2010 T_1: 2011-2014	T_0: 2010 T_1: 2014
Diff-in-diff	-46.6584	-62.732
Std err	(125.092)	(208.1)
Observations	1926	642
R-squared	0.261	0.260
Diff t(0)	575.6	563.5
Diff t(1)	528.9	500.8

7.3 Impact on investment in Intangible Assets

Intangible Assets are a second outcome variable to measure innovation (Box 7.1). This section presents the results of diff-in-diff and PSM models performed to investigate the potential impact of counterfeiting on the innovation performance of digital technology companies expressed by Intangible Assets.

Table 17 reports the results of alternative diff in diff models, which make use of different time intervals for the pre- and post- treatment periods. Regardless of the model specifications, the results indicate that the treated group (counterfeited firms) has an average larger volume of Intangible Assets compared to the control group, both before and after the treatment [Diff t(0) and Diff t(1)]. However, the difference of such differences [Diff-in-diff] is not statistically significant. Hence, the diff in diff model does not point at an effect, either positive or negative, of counterfeiting on the investment in Intangible Assets.

Table 17. Difference in difference models. Dependent variable: Intangible Assets. Treatment variable: infringement during years 2011-2013. Multiple time interval.

MODEL	II	III	I
OUTCOME	**INT ASSETS**	**INT ASSETS**	**INT ASSETS**
Time	T_0: 2010 T_1: 2014	T_0: 2010 T_1: 2014	T_0: 2009-2010 T_1: 2011-2014
Diff-in-diff	**-1.8992**	**7.6297**	**4.8579**
Std err	(10.177)	(9.567)	(5.610)
Sector and country dummies	No	Yes	No
Observations	42,338	42,338	138,306
R-squared	0.1088	0.2221	0.1129
Diff t(0)	366.7	329.9	363.2
Diff t(1)	364.8	337.6	368.1

Table 18 reports the Average Treatment Effects (ATE) estimated by the PSM model, where the growth rate of Intangible Assets over the period 2011-2015 was used as an outcome variable. This model compares the dynamics or the treated group against a selected subset of peer companies. The results suggest a small negative impact of counterfeiting on the investment in Intangible Assets, but this effect is not statistically significant at the conventional confidence levels.

Table 18. Propensity score matching and Average Treatment Effects. Model based on 5 nearest matches on ex-ante data. Outcomes variable Intangible Assets.

Models	I
Outcome Variable	**Growth rate of Intangible Assets (2011-2015)**
Average Treatment Effect: (Infringed vs. Non Infringed)	-0.5820
Std. Err	(0.368)
P-value	0.114
Observations	5,301

The joint analyses of the different the models on the innovation variables does not indicate a clear average impact of counterfeiting. The digital technology companies that were affected by counterfeiting on average increased their patent portfolios during the observation period, but less than the digital technology companies that were not affected by counterfeiting. However, the result is not robust to the inclusion of control variables and to the adoption of alternative measures of innovation performance (Intangible Assets).

8 Conclusions

8.1 Methodological caveats

Before moving to a comprehensive discussion of the evidence derived from the statistic and econometric analyses, it is important to highlight a set of methodological caveats. Such caveats are related to both the characteristics of the data and the nature of the analysed phenomenon and call for the importance of future extension of the analyses on different and possibly larger sets of data.

First, as evidenced in section 3.5.1, counterfeiting is only a partially-observable phenomenon, because seizures likely represent a potentially small fraction of true instances of counterfeiting. It is not possible to exclude that some of the companies included in the control sample (both the paired and unpaired sample) were affected by counterfeiting not recorded in the data. However, in this regard, it has to be noted that this potentially confounding effect would go against the evidence provided of the negative growth rate of Operative Margins.

Second, the detection of counterfeits and the number of seizures performed might be due at least in part by an active role played by firms in enforcing IPRs and enacting anti-counterfeiting action (Wilson and Sullivan, 2016). For example, it is possible that some companies spend considerable money to perform independent investigations that result in more seizure cases of the prosecution authorities. If this is the case, the inclusion of companies in the treatment sample may be endogenous to the costs that the companies incurred.

Third, for this study the data on seizures are available only for the years 2011-2013. This might generate clear issues in the identification of pre/post treatment periods for all the econometric models, because it is not known if and to what extent counterfeits existed before 2011 and after 2013.

Fourth, digital technology goods span a wide range of sectors. This implies the presence of significant heterogeneity among infringed companies and in the functioning of the respective markets (e.g. price elasticities; incidence of deceiving vs non-deceptive counterfeited goods; approaches to enforcement). Moreover, most of the companies analysed have a broad product range, for which it is impossible to disentangle economic performance (e.g. Operating Revenues, Operating Profits, assets). It is possible that the analysis did not observe effects that would instead be visible with product-level data. This calls for repeating the analysis with measures the product-level databases.

Fifth, counterfeiting likely targets incumbents and market leaders, which could lead to a spurious association of the intensity of counterfeiting activities and company performance both before and after the window of observation. This problem was partly mitigated with the use of diff-in-diff and PSM methods. However, the digital industry, particularly in the electronic consumer segment, is characterised by a significant market concentration with few large corporations accounting for the majority of the market. For such companies the identification of an appropriate comparable company is difficult, thus lowering the efficacy of the mitigation strategy.

Despite the limitations, the report offers the first assessment of a largely unexplored phenomenon, i.e. the impact of counterfeiting activities on the economic and innovation performance of companies, investigated at the firm level and on a global scale.

The econometric analyses presented herein and the limitations just discussed invite additional studies to repeat and expand the current analysis, possibly with the use of different and enhanced data and with mixed qualitative/ quantitative empirical strategies.

8.2 Summary and discussion

The theoretical literature, as well as the common wisdom, suggest that counterfeiting harms the economic and innovation performance of companies. However, a lack of reliable firm-level data has until now prevented the accomplishment of large-scale empirical investigations on the effect of counterfeiting. Furthermore, the theoretical literature has also hypothesized that counterfeiting might, in some conditions, generate positive spillovers for companies, potentially due to indirect advertising and/or widespread distribution that creates advantage positions in markets with network economies.

The goal of the present study was to provide the first comprehensive investigation of the impact of counterfeiting activities on both the economic and innovation performance of companies active in the area of digital technologies. To achieve this goal, a new firm-level database was built. The sample included only digital technology companies, 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 window of observation includes years from 2009 to 2015. The data have limitations, but they are at present a unique source of information that combines counterfeiting activities with financial and innovation data at the firm-level and on a global scale.

The analyses indicate that counterfeiting targets specifically highly profitable companies, with high propensity to innovate. Indeed, digital technology companies are more likely to become target of counterfeiting when they have larger Operating Revenues, and when they perform at a higher level in terms of profitability (return on total assets), prior to the window of observation. Target companies also have on average larger patent portfolios, prior to the observation of counterfeiting activities.

European digital technology companies are overall less likely than companies located elsewhere to be targeted by counterfeiting. This effect is present after controlling for sector and size of the firms, hence net of potential structural differences between EU and non-EU based firms.

The analysis of the impact of counterfeiting is complex and affected by a number of methodological problems caused by the endogeneity of counterfeiting with respect to company performance. The methodological problems were mitigated in part by the use of appropriate estimation strategies, including difference-in-difference, propensity score matching, and instrumental variables estimates.

Results from impact analyses indicate lower growth rates of operating profits for digital technology companies targeted by counterfeiting with respect to control samples of firms not affected by counterfeiting. In particular the econometric models provide evidence of a negative impact of counterfeiting on both EBITDA (Earnings before interest taxes depreciation and amortisation) and EBIT (Earnings before interest taxes).

The data reveals only a weak negative impact on operating revenues, with limited statistical confidence. Conversely, the impact on the Operative Margins is statistically significant and very robust, regardless of the outcome variable used (EBITDA or EBIT), the estimation techniques, and the model specifications. There is no robust evidence that counterfeiting is associated to statistically significant differences in the investment in fixed assets.

Concerning the innovative performance, the study finds that the companies affected by counterfeiting had larger patent portfolios compared to those not affected by counterfeiting prior to the observation of counterfeiting events and that this difference reduces over time. However, the relative decrease is not statistically significant, when we control for potential confounding factors. Hence it is not possible to derive the presence of a significant impact of counterfeiting on the patenting rates. Furthermore, there is no observable effect on the investment in intangible assets between companies affected and not affected by counterfeiting.

In conclusion, the study shows with considerable certainty that counterfeiting is associated to a worsening of the economic performance of the digital technology companies. The digital technology companies affected by counterfeiting had on average a worse dynamic of operating margins in comparison to the digital technology companies not affected by counterfeiting in the same years.

Conversely, the study shows no evidence clear of counterfeiting on innovation performance. The dynamic of innovation performance of companies targeted by counterfeiting, as measured by the number of new patent families filed and by the level of Intangible Assets, were overall comparable to those of digital technology companies not affected by counterfeiting.

The results of lower Operating Profits can be explained with some of the evidence reported by prior studies, which indicated that the companies targeted by counterfeiting react by investing in the differentiation of the product range and by enacting anti-counterfeiting practices, such as investing in conspicuous packaging, and in certifications of origin, or in other procedures aimed at limiting the circulation of counterfeits (Staake et al., 2009; Holliman and Memon, 2000; Siror et al., 2010; Li, 2013). The present study expands prior studies by showing that, collectively, these strategies may contribute to lower the profitability of targeted companies, as expressed by their Operating Profits, and are consequently harming companies targeted by counterfeiting.

The analyses performed exclude with considerable certainty the existence of any positive spillover effects of counterfeiting on the performance of the affected digital technology companies, which were hypothesised by the theoretical literature (Grossman and Shapiro, 1988b).

8.3 Future research and conclusions

The study has limitations, which invite further investigations.

First, the study considered only a limited time window. Future studies should replicate the analysis with extended time-window in order to capture medium-to-long term effects of counterfeiting. Second, this study showed a negative effect of counterfeiting on economic performance but could not estimate the magnitude of this effects. Future analyses could advance the understanding of the effects of counterfeiting by using product-level data, which can provide insights on magnitudes. Third, the study considered only digital technology companies. Caution is required in generalizing the findings beyond this industry. More analyses on different industries and different sets of data are needed to assess the degree to which these findings could be generalized. Forth, due to data limitations, this study did not investigate the impact of counterfeiting on R&D expenditures, calling for future analyses to close this gap. Finally, data limitations highlighted in section 3.5.1 suggest that more analyses based on different measures of counterfeiting and different sources of economic and innovation performance would be important to assess the robustness of the estimates.

Despite its limitation, this study is the first that provides a clear and rigorous evidence about the effect of counterfeiting. It shows that counterfeiting harmed the economic performance of targeted digital technology companies, by reducing their Operating Profits. There is no statistically-significant evidence that counterfeiting harms also the innovation activities of companies, but this result is not robust, thus the study cannot exclude that counterfeiting may induce a negative effect on innovation. Finally, the study rules-out with considerable certainty the presence of positive spillover associated to counterfeiting. Indeed, at least for what concerns digital technology companies, there is no evidence of any positive effect of infringement on sales of original products.

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