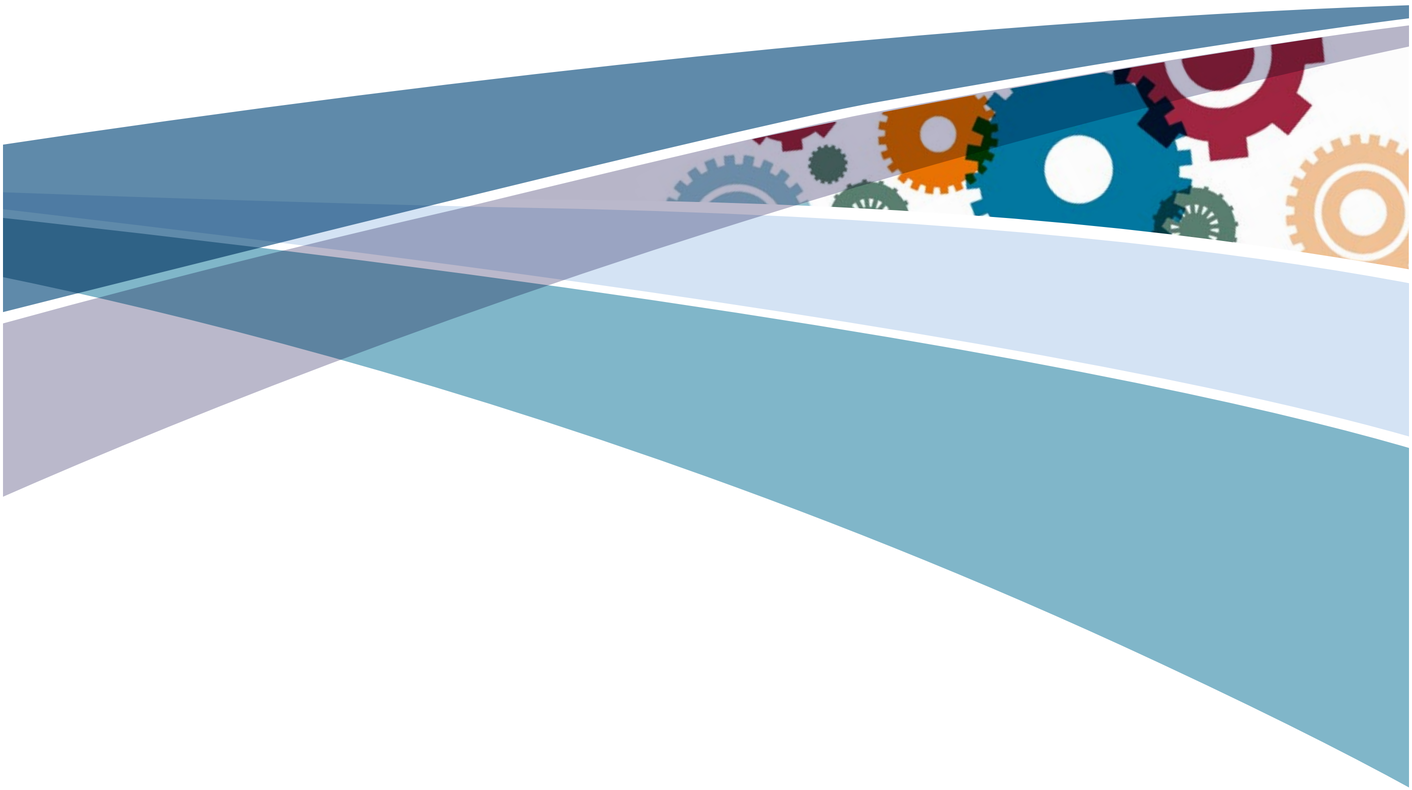
Intellectual
Property
Office

UK Trade Mark Demand: An Analysis



Research commissioned by the Intellectual Property Office and carried out by:

University of the West of England and Belmana Ltd

February 2017

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Findings and opinions are those of the researchers, not necessarily the views of the IPO or the Government.

2017/01

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We acknowledge the helpful comments throughout the study from the IPO steering group: Matthew Evans, Peter Evans, Pippa Hall, Mary-Anne Venables and Duncan Wearmouth.

ISBN: 978-1-910790-26-7

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Published by The Intellectual Property Office
February 2017

1 2 3 4 5 6 7 8 9 10

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This publication is available from our website at www.ipo.gov.uk

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Executive Summary

The Intellectual Property Office (IPO), an executive agency sponsored by the Department for Business, Energy and Industrial Strategy (BEIS), is the UK body responsible for registering trade marks (TMs), patents, designs and copyrights. Registration helps firms, designers and inventors to protect their intellectual property from unauthorised use by others and facilitates trade in these rights. A trade mark can be anything that defines a brand, for example words, sounds, logos, colours or a combination of all of these.

Faced with a very high increase in trade mark applications, the IPO has identified the need to forecast future trade mark applications to plan resource allocations. This report presents forecast results for 2017 and describes the approaches used to produce the forecasts.

A panel dataset based on individual trade mark filers is used to forecast the number of UK domestic trade marks filed with the IPO each year. International registrations under the Madrid Protocol have not been considered. The estimation uses the data in panel form, with the cross-sectional element focusing on the owner type (individuals, companies etc.). The forecasting separately models new applications for trade marks and the renewal of existing trade marks. For the renewals modelling, a key predictor is – unsurprisingly – the number of trade marks that are up for renewal. The preferred model specifications make the following predictions for future trade mark filings:

Forecast for new UK domestic trade mark applications and renewals

Calendar years	2014 (observed)	2015	2016	2017
New trade marks filed	50931	56319	61248	66793
Trade marks renewed	14697	25998	25730	28471
Trade mark classes renewed	26666	44394	45472	52023
Fiscal year	**2014/15 (observed)**	**2015/16**	**2016/17**	**2017/18**
New trade marks filed	50268	57551	62634	68190
Trade mark renewals	14506	25931	26415	27372
Trade mark classes renewed	26319	44663	47110	50315

Note: These forecasts are based on models flagged as “preferred” specifications below.

The “preferred model” was selected from six alternative specifications for new applications for trade marks and three models for renewals. The specifications differ due to the different segments modelled and variables used. The criteria used to select the model were goodness-of-fit, the performance of the model when used for recent years, and a practical consideration: the number of future years that could be forecast using the model.

Previous work has largely been based on the data held on the trade mark register. While having a long time-series and allowing individual owners to be identified, there is very limited information about the owner of marks. This study has firstly identified the type of owner. For companies, it has then linked the trade marks to data about the company owning the mark.

Since 2011, annual growth in the number of trade mark filings has been consistently above ten per cent, a level only seen once in the previous six decades (the 1980s). Most growth is derived from companies, though until the 1990s and the introduction of the European Union Trade Mark (EUTM), an important driver was also filings from foreign entities. Filings by individuals have also begun to contribute to growth in recent years.

The modelling includes looking at the impact of the EUTM on UK IPO filings. Results indicate that the introduction was associated with a fall in new UK trade mark applications each year as foreign businesses filed at a European level rather than in individual member states. A second policy driver is the extent to which recent simplification of the application process has encouraged trade marking. The evidence here is mixed as it is difficult to distinguish the effects of IPO policy from other drivers.

Structure of the report

Chapter 1 reviews the literature. There is literature on intellectual property rights and their use by individuals and businesses. The focus is usually on patenting and on the role of intellectual property in productivity and innovation. However, researchers have also considered trade marks, looking at both the effects of trade marking and the drivers for registering a mark. Regarding forecasting the number of new trade mark registrations, the literature is more limited. A set of approaches have been developed for patents and these are beginning to be used to analyse trade marking.

The underlying data about each mark, derived from the IPO's registration records, is described in chapter 2. The data comes from the live register of marks and the chapter reports the modelling of a history for each mark from its initial registration through all subsequent renewals. A key part of this study is linking each trade mark to information about the owner and the chapter describes this work. Owners are firstly categorised, with most identified as businesses or individuals. For businesses, steps were taken to link trade mark owners to a wider set of data about the business.

Chapter 3 describes recent trends in UK trade marking. There has been a growth in the number of new registrations in recent years. Chapter 4 describes the forecasting models used to predict new trade mark filings and renewals. The number of new applications and renewals were modelled separately because the two types of transactions are quite different, which is also borne out in the results.

The modelling finds that the number of new filings is quite persistent, in that last year's activity determines this year's to a significant degree. This finding is similar to other comparable studies and, like other studies, the modelling focuses on the annual change in activity. Macroeconomic variables, such as GDP and investment, are used to explain the change in activity and chapter 4 indicates the results of the alternative models. For renewals, the number of trade marks that are due for renewal each year is a predictor of the actual renewal activity that year.

Chapter 5 looks at the evidence on two policy areas: the introduction of the EUTM in 1996 and recent IPO policies to encourage trade marking. It also compares the findings in this report to those from a similar project commissioned by the EU IPO on trade mark and patent filings in Spain.

1. Approaches to Forecasting Trade Marking

This chapter reviews evidence about why businesses and individuals file trade marks. Trade marking in the UK is firstly outlined and then recent literature is reviewed. The literature highlights a strong link between trade marking by businesses and innovation activity. It provides a starting point to forecast trade marking activity and the chapter considers some recent work in such modelling.

As researchers have considered productivity and innovation, the actions taken by individuals and businesses to register intellectual property rights has attracted interest. A primary focus has been patenting but researchers have also considered the trade mark, looking at both the effects of trade marking and the drivers for registering a mark.

Regarding forecasting the number of trade marks that will be registered, the literature is more limited. However, a set of approaches has been developed for patents. The work is usually commissioned by intellectual property offices to support their operational needs. These approaches are beginning to be used to analyse trade marking as well.

Trade marking in the UK

Trade marks confer intellectual property rights that typically protect a name or logo. They serve to create brand identity, so that products are more easily distinguishable. They help consumers choose from different products, and producers to distinguish themselves from competitors and to protect against imitation.

In the UK, registration of a trade mark occurs through the Intellectual Property Office (IPO). Registration is for a period of ten years, after which the holder is entitled to renew the registration. While renewal is relatively straightforward, the application process provides an opportunity for the IPO to ensure the trade mark is suitable to be registered. It also allows others to contest the registration, especially if it is close to another holder's mark.

The recent steep rise in UK filing activity has been accompanied by several commentaries about the policy drivers. Explanations for the rise have included the IPO's marketing activity. The IPO is marketing its services to individuals and SMEs, raising awareness that protection is available and useful, and assisting applicants through the application process. IPO supports businesses considering IP protection through its "IP audits". These have provided people and businesses with the opportunity to look at what rights they have in place.

A further support measure has been the TM10 Programme. Under this programme, the IPO facilitated online filings without representation. Coupled with that, there has been a rise in online agents offering filing assistance at low prices. This has made access to IP even easier, while increasing costs only moderately.

The main international policy dimension has been the co-ordination between UK IPO and the European Intellectual Property Office, as well as other international organisations.

The EUTM was first proposed for Regulation in 1980, but it was not until 1st April 1996 that the first EU trade mark applications were processed and the register started (as Community Trade Marks). An EUTM (EU trade mark became the name of Community Trade Marks on 23rd March 2016) is a trade mark which is pending registration or has been registered in the European Union as a whole (rather than on a national level within the EU). The application would be registered with the European Union IPO (EU IPO). European co-ordination has occurred in the context of international work. The international system was modernised in 2004 with the Madrid protocol, which was established in conjunction with the European Community Trademark, and the two systems are closely linked to facilitate worldwide IP protection.

The registration options open to a company with an international presence are to apply directly to individual Intellectual Property Offices, including the EU IPO which gives a Europe-wide mark, or to apply to the international co-ordinated route under the Madrid system. The latter uses the processes of the trade marker's home organisation and then extends the application process to other countries. These "international applications" have become a significant portion of IPO's workload. However, businesses often do prefer the direct route of application in several countries. This is because the success of an application in one country is then independent of other applications, whereas an international application refusal would mean a refusal across all jurisdictions.

Forecasting trade mark applications

Several Intellectual Property Offices have developed trade mark forecasting models. During the past few decades, the offices have seen a rise in the number of marks registered. Forecasting this is important so that registration bodies can plan their work and allocate resources. Hidalgo and Gabaly (2013) provided an overview of the types of models, reproduced below in Table 1. Many models use Autoregressive Integrated Moving Average (ARIMA), a technique that projects future values of a series based entirely on its own inertia.

A key influence on approaches to forecast trade marking is the parallel work forecasting patent applications. Adams et al (1997) focused on the United States and was the first attempt at aggregated predication of the number of patents. Hingley and Nicolas (2004) provided the first models for the European Union; they also reviewed several studies of forecasting models. To date, most researchers have learnt from and adapted the methods of patent forecasting with mixed success.

Bock et al. (2004) provided a first attempt at forecasting trade marks. In 2001, the Swiss Federal Institute of Intellectual Property (IPI) was faced with a sudden and unexpected decrease in trade mark applications. This fall highlighted that there was no data or modelling with which to predict trade mark applications and the resources needed by an IPI to meet demand for its services.

Bock et al. (2004) proposed a forecasting model based on state-space models with and without explanatory variables. State-space models are a subset of the ARIMA models, focusing on modelling an underlying process (the state) and then the behaviour around this. The authors used a standard ARIMA model with trend, seasonal and random components, then added variables for external drivers. The reliability of results was improved slightly by adding economic variables such as the Dow Jones index and the Swiss consumer confidence index. Their theory and methods were reliant on general specifications as the authors considered that too little was understood about the relationship between trade mark filings and potential explanatory variables. The authors examined applications received between 1992 and 2002.

Table 1: Forecasting approaches for intellectual property

Source	Scope	Description
World Intellectual Property Office	All types of IP	Combination of time-series, econometric and survey-based models
European Union Intellectual Property Office (EU IPO)		Simple trend models, time-series and econometric models, first application transfer models, ARIMA transfer function methods, and surveys amongst clients and consensus of experts.
United States Patents and Trade Marks Office (USPTO)	Patents and trade marks	Simple trend models, exponential smoothing models, ARIMA and econometric models with regressors, client surveys and Delphi method. Used for predicting costs and fee income
Japanese Office of Patents and Trade Marks (JPO)	Patents	Client surveys and time-series prediction models.
Swiss Federal Institute of Intellectual Property (SFIIP)	Trade marks	Structural models in state-space form both with and without regressors (Dow Jones, SMI, SPI and Swiss consumer index as regressors).
Korean Intellectual Property Office (KIPO)		Model of trend extrapolation based on the application of average inter-annual growth rates.
Hidalgo & Gabaly (2013) for the Spanish Patents and Trade Marks Office	Trade marks	ARIMA, polynomial distributed lag model (PDL), intelligent transfer function model (ITF), including exogenous variables (GDP and R&D expenditure have most explanatory power).

To test the model, the authors checked if the model would correctly predict aspects of the historical trend, in this case the period 1992-2001. The model failed to predict the "extraordinary situations" but was relatively accurate for "normal and average situations". There was one particularly steep increase in applications in the year 2000, which the model failed to predict. This might have been a result of a decrease in application fees combined with the dot-com boom, two idiosyncratic factors that would be hard to pick up by a general model.

A more recent contribution comes from Hidalgo and Gabaly (2012). The research was conducted for the Spanish Office of Patents and Trade Marks, modelling both patents and trade mark applications in the period 1979-2009. The models developed are used to predict the change in the number of patent and trade mark applications, supporting the Office's planning. The focus of the models is forecasting the short-term: for a horizon of three years. One cross-section and three time-series models were tested.

All time-series models can explain about 50 per cent of the variation in trade mark applications. However, the trade mark models fare much worse than those for patent applications, which can explain about 80 per cent of the variation. Taking other metrics for goodness-of-fit into consideration (mean squared errors, Bayesian information criterion), the authors concluded that the ARIMA(1,1,0) model is the most useful for forecasting.

Despite the success of using an ARIMA model, the authors, in a follow-up paper, sought to optimise their methods using further explanatory variables and more advanced techniques (Hidalgo & Gabaly, 2013). From a review of forecasting models used by other patent offices, they identified potential explanatory variables, relating to economic activity, R&D activity and stock market indices. Based on the availability of data and their strong correlations with trade mark applications, they selected gross domestic product (GDP) and the industrial production index. Models cover the period 2011-2014 and a focus was to consider which of the different models tested, alongside the previous ARIMA model, are best at forecasting. The models used are a simple econometric model with a predictive lag variable, a polynomial distributed lag (PDL) model and an intelligent transfer function (ITF) model.

The recent work departed from ARIMA by seeking to widen the set of drivers for registration activity beyond past activity. The next sections look at potential drivers.

Connecting intellectual property and innovation

Economic theory gives insights into why trade marks exist and how they stimulate innovation. This literature is at the junction of microeconomics and management theory, for example, explaining the role of trade marks in driving firm value and signalling to investors. There is also an empirical dimension to this research, quantifying the reasons for a business to trade mark and understanding the effects on firm performance of the intellectual property. This section reviews some of this work, particularly exploring if and where it can assist in forecasting trade marking activity. Overall:

- There is a link between innovativeness, productivity and intellectual property.
- However, the link between firm level innovation activity and trade marking is not complete enough for a forecasting model. Causality is very likely to be two-way and measuring innovation remains very complex requiring specific data to be collected.

- Strategic behaviours – such as companies filing marks for catchy names restricting branding options for others – are unlikely to have significant effects on the total trade mark registration activity.

Greenhalgh et al (2011) found that more productive UK firms tend to trade mark more. Their study then explored causality and suggested the correlation may be spurious. Further analysis showed that the productivity effect can be explained by differences in innovativeness between firms. Innovation can be both a driver and outcome of trade marking, making it difficult to predict which businesses trade mark.

Such research does then differentiate between different forms of innovation, such as product, marketing or process innovation. Millot (2011) showed that innovating firms are more likely to trade mark than non-innovating ones. However, product-innovating firms in high-tech manufacturing sectors use patents more than trade marks; the reverse is true for firms in the service sector, and to a lower extent for firms in the low-tech sectors. Flikkema (2010) found that it is often a mix of different innovation activities (between non-technological, technological, marketing, process, service, and product innovation) that form the basis for the registration of a trade mark. The evidence uncovers how trade marks can be used to protect against imitation, for marketing purposes, and as a signal to external partners (Block et al., 2015).

Von Graevnitz (2012) investigated a phenomenon that is seemingly unrelated to targeted protection of property rights: trade mark cluttering. This is defined as the registration of trade marks that are overly broad, just to block others from registering that mark. They argue that this behaviour can become systemic if firms competitively try to snatch catchy names from their competitors to leave them at a disadvantage in marketing their products. However, they did not find any evidence for this hypothesis in the UK. In contrast, in a similar study on patent “thickets”, Hall et al (2013) found evidence for their existence, acting as a barrier to entry in some technology areas.

The key to studies on innovation is that they collect survey data specifically to look at trade marking activity. The evidence from such studies therefore provides an understanding of the differences between businesses, but proves difficult to generalise across the entire economy or to model without data that have been purposively collected. The next section looks at studies that use data that is more readily available.

Characterising the trade mark owner

The drivers for trade marking can sometimes be linked to who owns trade marks. Such evidence can also be based on data that are generally available or routinely collected as trade marks are registered. It is then more likely to be useable in a forecasting model. There are patterns emerging in the literature analysing such drivers:

- Those who already own a trade mark are more likely to subsequently register a trade mark.
- Large businesses are more likely to trade mark than smaller and then register more marks per owner.
- Some industries are more likely to trade mark compared to others.

Looking at who registers a trade mark, it is often noted that most trade marks are filed by SMEs. This reflects the large absolute number of such businesses as larger businesses are more likely to forecast than smaller ones. Analysis shows that the propensity to trade mark increases with firm size (Amara et al., 2008; Millot, 2011). Also, the number of marks registered by each business increases with size.

There seems to be a U-shaped relation with age. Firms tend to trade mark soon after incorporation, and then again at a more mature age, perhaps after some growth (Mamede et al., 2012; Millot, 2011). The age of a trade marking business is related to a higher rate of trade marking amongst the businesses that have a history of trade marking. Mamede et al. explored this, considering the effect of being a trade mark applicant in previous years on trade marking activity. The use of trade marks is a somewhat idiosyncratic feature of firms: for reasons that are not captured by other characteristics, recurrent trade mark users are more than seven times more likely to apply for a trade mark than other firms (Mamede et al., 2012).

Research generally finds the industry of a business is correlated with trade marking. Among French firms, the use of trade marks is higher in advanced technology and knowledge intensive sectors, particularly the pharmaceutical, chemical products and insurance industries (Millot, 2011). Trade marking is also linked to the use of other intellectual property registration such as patents, especially in high-tech and knowledge-intensive industries (Amara et al., 2008; Flikkema et al., 2010).

Trade marks have also been investigated as a signalling device to investors and their role in driving firm valuation. Sandner and Block (2011) argued that a company's portfolio of trade marks contributes substantially to the market valuations of companies – more so than patents. The work allows for the quality of 'knowledge' in the company, as represented by capitalised R&D expenditure, and its findings still are maintained. Krasnikov et al. (2009) analysed the drivers of trade mark applications from the perspective of marketing and independently came to the same conclusion as Sandner and Block (2009). They also noted that trade marking activity must be repetitive to achieve the maximum benefits.

Looking at the amount of venture capital (VC) start-ups receive, Block et al. (2015) found that firms with trade marks received more VC, especially in early funding rounds. Furthermore, they identified a complementarity between patents and trade marks. Firms that apply for both forms of IP receive 35.4 per cent more funding than those who apply only for one form. They hypothesise that it is the combination of signalling technological innovation as well as market access that is especially appealing to investors.

2. Data Sources for Trade Mark Forecasting

This study has benefitted from a snapshot of the IPO's trade mark register. As the register only gives a one-off picture, a history for each mark from its original application through any renewals has been constructed. Several other variables have been linked to this data, primarily by identifying the type of owner. A further data source has focused on those trade mark filers that are UK businesses, where the trade mark can then be linked to business data.

The previous chapter indicates that the possible drivers for trade marking are numerous and so the data needed to model trade marking is an important component in forecast quality. An initial set of information about trade marks is the records associated with each mark in the register. This chapter describes the underlying data about each mark and the modelling performed to provide a history for each mark about registration and any subsequent renewals.

The discussion then turns to approaches to identify the trade mark owner. The owners are mainly individuals and businesses. A categorisation of each mark by the type of owner is firstly undertaken. A complex set of steps have then been undertaken to link trade mark data to a wider set of data, primarily microdata about individual businesses.

Trade marking data

This study uses a snapshot of the current trade mark register. It lists about a million trade marks, including all the domestic live trade marks and those where the registration has lapsed but were alive during 2002. It also indicates trade marks that are either in the process of being registered or have recently been refused registration. Some marks have a long history, with trade marks extending back over a hundred years. However, the removal of trade marks that expired before 2003 means that the history is incomplete for trade marks filed before 1988 that were not subsequently renewed. Furthermore, trade marks registered under the Madrid Protocol are not included.

The current owner's name and address are provided for each trade mark. The original date of application is also provided and the date on which the mark expires. Where the trade mark is no longer live, the expiry date will have passed; live trade marks will have an expiry date in the future. The trade mark is classified as part of the application process, defining the broad use made of the trade mark. For example, a logo might be for the class of textiles and luggage. A trade mark can be registered for several classes at once and, at renewal, the classes can be changed but only by removing classes, as adding would necessitate a new application.

A key characteristic of a trade mark is the length of time for which it gives the holder a property right. An applicant applying today would need to renew after ten years, or the mark would lapse. The renewal horizon was changed to the current regime in April 1995. All trade marks registered earlier were initially registered for 7 years and then for 14 years after each renewal.

The trade mark register has the next renewal date and the original application date. These can be combined with the information on renewal periods to model the history of renewals of each of the trade marks older than ten years. Thus, for each trade mark, the series of register-related transactions with the IPO, starting with the application and then each renewal, can be mapped out. This history of each trade mark means a "stock-flow" model covering several decades of trade marking activity can be constructed. This means that key characteristics of the register – the number of live marks, the number of new applications, the number of renewals and the number of marks that lapsed – can be estimated on a quarterly and annual basis. Further, various cuts to this data can be derived, such as by the class of the mark. More details on the construction of the renewal dates are provided in appendix A4.

Improving the ownership details

The dataset provides the name and address of the owner and therefore is relatively limited in the characteristics of each owner. The owners of each mark can be a business or an individual or numerous other types of organisations. Further, holders may own multiple trade marks, something which the register cannot readily identify.

To gain more information about trade mark owners, firstly, names were standardised, particularly harmonising common terms in organisation names and removing unnecessary characters (e.g., punctuation). Owners that had multiple trade marks were identified and a list of owners compiled, consolidating the trade mark register.

A second stage prepared the data for linking to company databases, primarily the Companies House register. Individuals and institutions not registered in Companies House can apply for trade marks as well. The second stage sought to extract from the trade mark owner lists all but the entities with limited liability. This was done by matching the words that make up the names of the owners to databases of organisational descriptors, personal names and surnames and then identifying whether an owner is a person or group of people.

Individuals were singled out by matching trade mark owners with a database of common given and family names. Educational, public sector and other institutions were identified by searching for key words, such as "university" or "council". Similarly, trusts, building societies and associations were picked out. Further, the trade mark owners that had addresses outside the UK or who specified their country other than Great Britain were marked as international holders.

This stage was important for two key reasons. Firstly, as a category, the individual filer is significant and identifying each proves very useful in later modelling. Secondly, the scale of the database necessitates matching be done automatically with company registers. Automatic matching to any companies' database is likely to deliver false matches if individuals are not removed and if the list includes a lot of entities that are not on the register.

Matching to the Companies House register can exploit a strength of the IPO trade mark register: that the owner fields are quite accurate with owner names generally not misspelt. This meant that exact matching on standardised name and post code proved quite successful. Then exact matching on name alone was also undertaken. This helps matching companies that changed their address after applying for a trade mark, but increases the risk of "false positives". Matching was also undertaken using OpenRefine. Manual matching was also used, especially where it was apparent that a number of trade marks were held by the same company but that company had not been identified on the Companies House register automatically.

A detailed account of the matching process can be found in Appendix A1. Throughout the matching process, clerical matching was performed on random samples for quality assurance. The quality checking determined how well a particular matching approach has worked, especially in terms of not matching too many records falsely. Secondly, quality checks highlighted systematic failures in matching and this informed an improvement to the matching processes used.

Of 347,596 trade mark owners, 171,761 were identified as UK companies. 158,802 trade mark owners were matched to a Companies House registration number. Those not identified as companies were further characterised as individuals, educational institutions, other institutions, public sector entities, and foreign entities. This still leaves a number of owners unidentified, and those were grouped together as a final owner type.

Panel data with macroeconomic and other trade marking drivers

The stock flow model provided an annual database of transactions (application and renewal primarily) for each mark, far richer in detail than required for a forecasting model. The study therefore constructed panels of data that aggregated the microdata evidence derived about individual marks.

The data was first split into two. One focused on the new trade mark applications. The focus of the second was the renewal of marks each year.

A first pair of panels provided a long time-series using only the trade mark data focusing on the owner type. It divided the data into nine categories of owner (individual, company, etc.). For each year and each category, the number of new trade mark applications and renewals was totalled. For the panel focusing on renewals, a variable was constructed using the stock-flow model aggregating the number of trade marks that were due for renewal each year.

However, coverage is incomplete before 1988, and control variables are less available. The variables available for this modelling were largely macroeconomic series available from official sources. The modelling in the next chapter uses official macroeconomic indicators produced by the ONS. The focus has been business investment and GDP, because these are then forecast regularly by the Office for Budget Responsibility (OBR). In developing more long-term views of trade marking activity, the OBR long-term GDP and investment forecasts may then be integrated into models.

A further pair of panel datasets were prepared which had a short time-series but were more detailed in terms of the cross-section.

Linking the businesses to Companies House allows the firm-level data held on the Companies House public register and commercial databases – such as the FAME database of company accounts – to be used in the modelling. In the econometric work, the trade mark data are used at an industry level, with those businesses that are active trade markers distinguished from the wider population.

3. Recent Trends in Trade Mark Activity

The trade mark data described in the previous chapter, when combined with information about the timing of renewals, provides a long historical dataset about trade marking activity. This chapter explores that data highlighting recent trends on applying for trade marks.

Trade mark filings are segmented by the type of filer, date of initial filing, and by first and repeat filings. For type of filer, companies, individuals, educational institutions, public sector entities, other institutions, foreign owners and unidentified others are distinguished by analysing owners' names. While the trade mark data go back to the 19th century, estimations here use only data starting in 1950.

Our findings are that:

- Since 2011, annual growth in the number of trade mark filings has been consistently above ten per cent, a level only seen once (the 1980s) in the previous six decades;
- Most growth is derived from domestic companies, though until the 1990s and the introduction of the EUTM, an important driver was also filings from foreign entities;
- Filings by individuals have also begun to contribute to growth in recent years;
- The growth is also centred on a rise in the number of first time files, rather than filings per owner increasing or changes in the trade marking of entities with a history of holding marks;
- In terms of behaviour by cohort, those who filed for the first time before 1980 show the highest rate of follow-up filings;
- By industry, wholesale and retail trade, manufacturing, information and communication, and professional, scientific and technical activities are the largest trade markers.

Exploratory data analysis

Table 2 gives the number of trade mark filings over different periods, as well as annual growth rates. Since 2011, annual growth has been consistently above ten per cent, a level previously only seen once, in the 1980s. Because of a change in trend due to the introduction of the Community trade mark in 1996, numbers are also reported excluding foreign filings. However, the overall pattern remains the same.

Table 3 breaks down the growth rate by the type of filer. It shows the percentage of growth in trade mark filings that can be attributed to the change in filings by a particular group (computed as the year-on-year change in filings by a particular group divided by the total change). The shares reflect positive contribution to growth as positive, with a negative share meaning that the contribution depressed growth. In periods where trade marks decline in total, such as 2000s, shares of declining categories exceed the growing ones.

Overall, most of the growth is explained by the growth in filings from companies. Until the 1990s, an important driver was also filings from foreign entities. However, these fell sharply after 1996 at the time of the EUTM's introduction. While it could have been expected that filings from domestic firms would fall as well, the data show no such trend. Filings by individuals have seen remarkable growth in recent years.

Table 2: Number of UK domestic trade mark filings

	1950-79	1980s	1990s	2000s	2010	2011	2012	2013	2014
Total	3,750	13,223	25,936	24,341	30,342	36,322	40,224	46,173	50,931
Total excl. foreign	1,718	5,999	13,701	19,745	26,338	32,030	35,957	42,045	46,303
Growth	0.0%	13.4%	7.0%	-0.6%	4.5%	19.7%	10.7%	14.8%	10.3%
Growth excl. foreign	-0.1%	13.3%	8.6%	3.7%	5.9%	21.6%	12.3%	16.9%	10.1%

2010-14 are annual totals and year-on-year growth; for periods, estimates are annual averages.

Table 3: Contribution to growth in filings by different types of owners

	1960-79	1980s	1990s	2000s	2010	2011	2012	2013	2014
Corporate	37.3%	43.5%	49.1%	205.5%	73.3%	61.5%	74.2%	34.1%	87.4%
first-time	7.1%	13.7%	18.9%	184.1%	59.4%	42.0%	58.3%	25.6%	62.3%
repeat	30.2%	29.8%	30.2%	21.5%	13.8%	19.4%	15.9%	8.6%	25.0%
Individual	1.4%	2.6%	8.5%	144.9%	26.6%	26.2%	15.3%	66.9%	7.6%
first-time	1.1%	2.2%	7.2%	114.1%	20.1%	20.7%	9.6%	60.5%	-7.4%
repeat	0.3%	0.5%	1.3%	30.7%	6.5%	5.5%	5.7%	6.4%	14.9%
Foreign	60.7%	52.7%	39.4%	-478.8%	-9.9%	4.8%	-0.6%	-2.3%	10.5%
Education	0.1%	0.0%	0.4%	1.7%	0.6%	0.3%	2.3%	-0.5%	-0.8%
Institution	0.2%	0.6%	1.3%	1.6%	1.5%	1.1%	0.6%	-0.2%	1.3%
Public	0.1%	0.1%	0.3%	1.3%	0.3%	0.0%	0.5%	-0.4%	0.8%
Other	0.2%	0.4%	1.1%	23.8%	7.6%	6.1%	7.7%	2.4%	-6.7%
TOTAL	100%	100%	100%	100%	100%	100%	100%	100%	100%

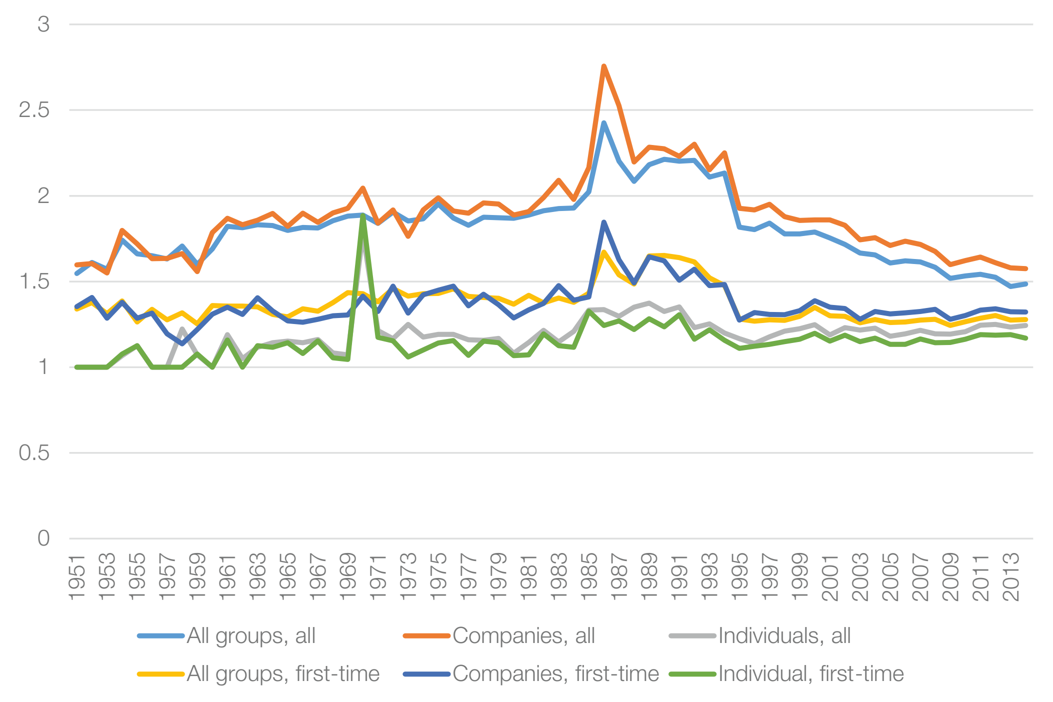
In the table, the corporate and individual filers are split up further by first-time and repeated filers. Historically, growth was driven more by repeat filers, represented mainly by large consumer goods and pharmaceutical corporations who tend to hold the most trade marks overall. In recent years, the trend has shifted to first-time filers, usually start-ups and SMEs. This may have resulted from increased IP production with businesses then seeking protection for these outputs. It may also reflect increased outreach by the IPO and its programme to simplify the application.

Growth in filings could not only be driven by more companies or individuals filing for trade marks, but also by an increased number of filings per filer. Figure 1 plots the average number of filings per filer for each year for different owner types.

Throughout, first-time filers had a lower number of average filings. In fact, most only apply for a single mark. After a peak in average filings in the mid-1980s, the filings per owner started to fall, so that it is now almost at the level of that of first-time filers at around 1.5 marks.

Two factors explaining this trend are the higher number of first-time filers overall, as well as the increased importance of individuals as filers. However, the average for companies has fallen as well, with SMEs rather than multinationals filing for many marks dominating the mix.

Figure 1: Average number of filings per filer

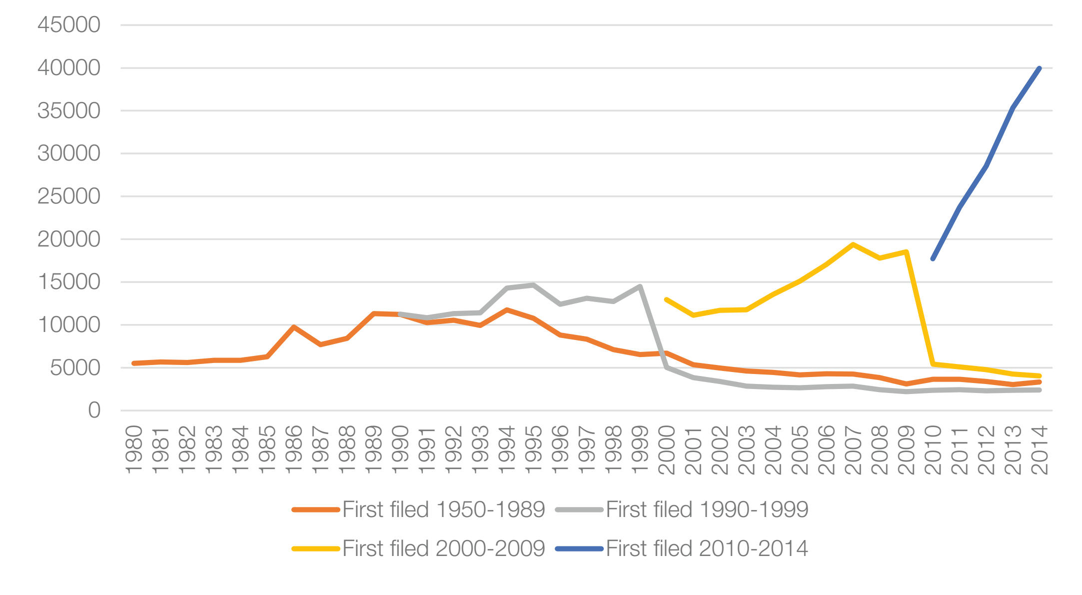


Analysing trade marking by cohorts and industry

Figure 2 looks at different cohorts of filers. A cohort is defined by the year in which an owner first filed for a trade mark. For example, the 1990-1999 cohort first filed for a trade mark during those years, and the chart shows the number of initial as well as subsequent filings by those trade mark owners.

For the 1990s and 2000s cohorts, follow-up filings are negligible. Those who filed for the first time before 1980 show the highest rate of follow-up filings. However, this is also a survival effect: the data only retain those owners who renewed their trade marks up until today and thus favour large companies who are still operating today and own a lot of trade marks. Crucially, older cohorts had almost no influence on the recent increase in trade mark filings. Even the 2000 to 2009 cohort contributed only a small fraction to the increase in filings witnessed since 2010.

Figure 2: Trade mark filings by cohort



This suggests breaking down the data further by first-time and repeat filings. This is done for companies and individuals separately in Figure 3. Up until 2009, Corporate repeat filers were the largest single group of filers. However, since then they have been overtaken by first-time filers. First-time filings from individuals have also markedly increased. This suggests that start-up activity and the increase in self-employment after the financial crisis might be driving the increase in trade marking.

A key innovation in this study is linking trade mark owners to company records. This allows the analysis to be further segmented by SIC codes. Filings by different industries are shown in Figure 4. The largest groups are G, C, J, and M, which represent wholesale and retail trade (including repair of motor vehicles and motorcycles), manufacturing, information and communication, and professional, scientific and technical activities, respectively.

Figure 3: First-time and repeat filings by companies and individuals

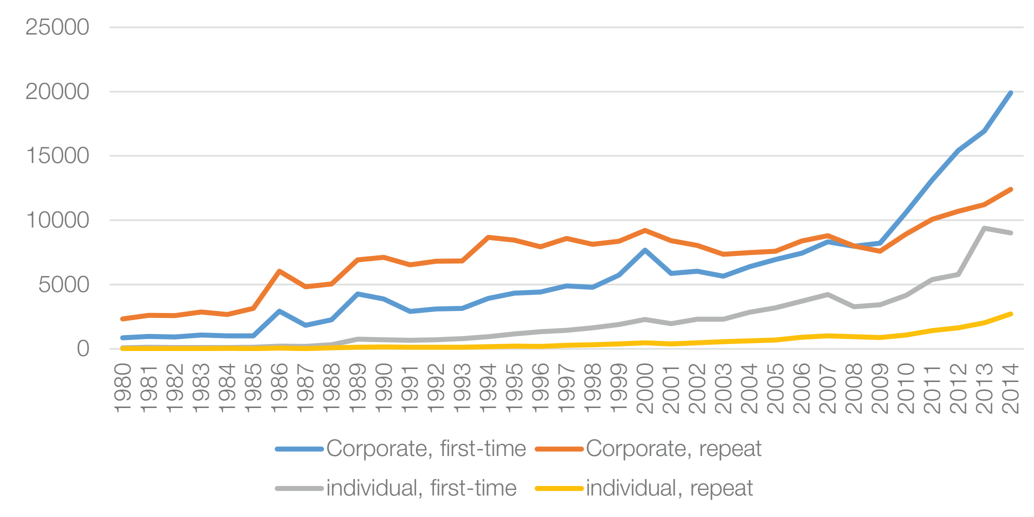
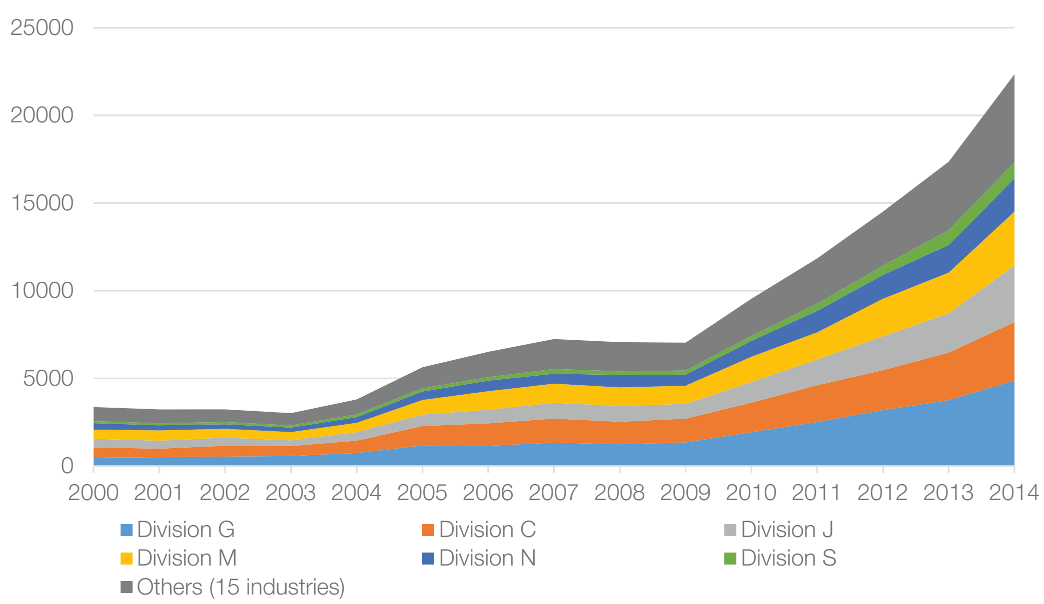


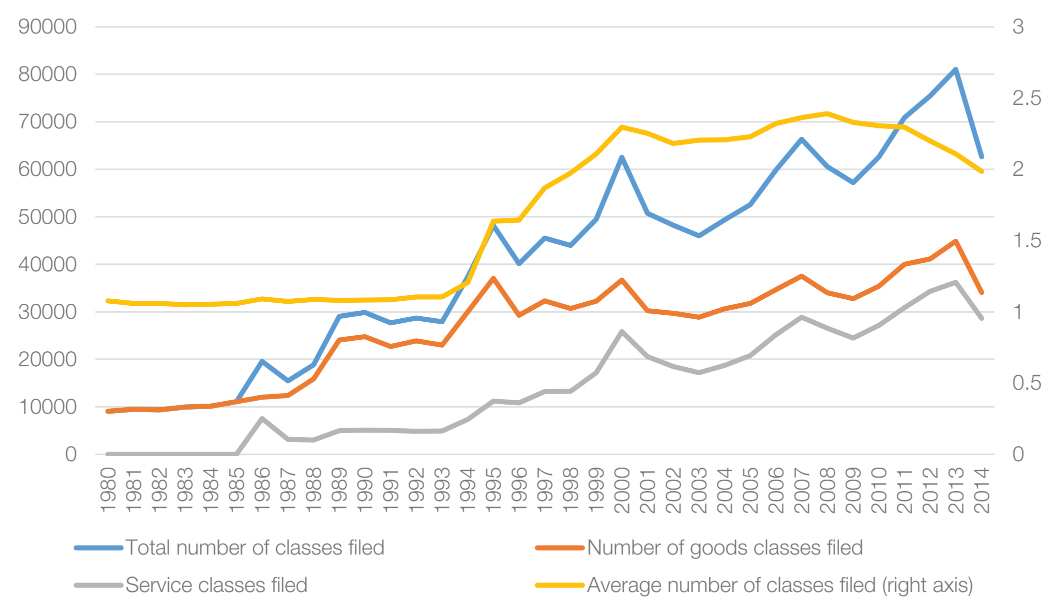
Figure 4: Filings by SIC code



Classes of trade marks

Trade marks can be filed in any number of 45 classes, 34 for goods and 11 for services. When renewing a trade mark, the owner can choose to re-register in less, but not more classes than originally registered. The database reflects only the classes registered at the time the snapshot was taken; coverage of classes in the database is not entirely accurate. Nevertheless, Figure 5 gives an overview of recent trends.

Figure 5: UK domestic trade mark filings by class



Paralleling the number of individual trade marks filed, the number of classes registered has also risen. However, the average number of classes filed per trade mark has slightly decreased, to about two from a peak of two and a half (right axis on the chart). Service classes were only introduced in 1985 and have since almost caught up with the number of goods classes filed. That their number is still lower could partly reflect that there are fewer classes for services available, so owners from the service industry are necessarily choosing from fewer classes.

4. Forecasting Trade Marking Activity

A panel dataset based on individual trade mark filings is used to forecast the number of trade marks filed with the IPO each year. The focus of this chapter is the estimation using panel data. The chapter describes six models estimated for new applications and two for renewals.

For the renewals modelling, a key predictor is – unsurprisingly – the number of trade marks that are due for renewal. The four models used for new applications differentiate between the type of filer (individuals, companies etc.) and, having linked company filers to business registers, further splits by the industry of each of the companies. Past filing behaviour is also used. This then allows variables to be used from official industry-level data and from firm-level data.

The preferred model specifications make the following predictions for future trade mark filings:

Table 4: Forecast new UK domestic trade mark applications and renewals

Calendar years	**2014 (observed)**	**2015**	**2016**	**2017**
New trade marks filed	50931	56319	61248	66793
Trade marks renewed	14697	25998	25730	28471
Trade mark classes renewed	26666	44394	45472	52023
Fiscal year	**2014/15 (observed)**	**2015/16**	**2016/17**	**2017/18**
New trade marks filed	50268	57551	62634	68190
Trade mark renewals	14506	25931	26415	27372
Trade mark classes renewed	26319	44663	47110	50315

Note: These forecasts are based on models flagged as “preferred” specifications below.

The chapter describes the forecasting models. Key points are:

- For modelling new applications, two models use the type of filer, adding up all applications each year made by seven types; a further four models then split the companies’ type by their industry with two using industry level data and two using firm level data focusing on large businesses.

- Past filing activity is a key driver: for new applications, the modelling has separated the behaviour of those with a history of trade marking from new applicants.

- For renewals, each year, about half of trade marks due to be re-registered are renewed, a key driver for forecasts.

The modelling finds that a year’s new trade mark application correlates with the activity in the previous year to a significant degree. Thus, as with other comparable studies, the modelling is undertaken focusing on the change in activity. Macroeconomic variables commonly used in forecasting, such as GDP and investment, are used in the modelling. For renewals, unsurprisingly, a good predictor is how many trade marks are due for renewal and this can be estimated precisely through modelling trade mark expiration dates.

Modelling strategy

The modelling approach uses an auto-regressive distributed lag model, which estimates the dependent variable – the number of trade marks filed or renewed – as a function of its own lags and the contemporaneous and lagged values of other control variables. The basic model thus looks as follows:

$$y_{it} = \sum_{j=1}^{p} \alpha_{ij}\, y_{it-j} + \sum_{j=0}^{p} \beta_j\, X_{it-j} + \mu_i + \epsilon_{it} \qquad (1)$$

where *y* is the dependent variable, *i* is the group identifier, *t* the time period identifier and *j* the lag identifier; there are *N* groups, *T* periods, and *P* lags. *X* is a vector of explanatory variables. μ_i are group specific fixed-effects and ϵ_{it} is a standard error term.

One difficulty arises when the time-series used are non-stationary. Panel unit root tests suggests that this is likely the case for the trade marking series. Detailed test results can be found in Annex A2. In this case, estimation of equation (1) would be spurious. Therefore, the model has to be modified to be estimated in differences:

$$\Delta y_{it} = \sum_{j=1}^{p} \alpha_{ij} * {}^{\Delta} y_{it-j} + \sum_{j=0}^{p} \beta_j * \Delta X_{it-j} + \Delta\epsilon_{it} \qquad (2)$$

Model estimation

The model specified above is designed for estimation of panel data. Since data on individual trade marks are available, they can be aggregated into panels in several different ways. Thanks to the linking work undertaken in this study, it has been possible to refine such groupings, firstly by placing different types of filers together, by companies, individuals, etc., as already shown before.

Most of those identified as companies could also be linked to a Companies House record (details in appendix A1). These could then be grouped by SIC code, aggregated to the European Union-wide NACE letter sections. Furthermore, for large companies, detailed company account data were available, which have also been used for estimation. However, the classification by SIC code proved most useful. It turns out to be very hard to predict company behaviour on the micro level, probably because many of the drivers for trade marking are unobserved. However, in the aggregate, reasonably accurate predictions about trade mark filings can be made.

Table 5 gives an overview of the control variables being used. Detailed sources can be found in the list of references in the appendix. These control variables are generally only available on an annual basis, so that forecasting is also undertaken in annual intervals. The trade marking data show some seasonal variation, but this tends to be minor, especially in comparison to the strong upward trend of recent years.

Box 4.1: Considerations in choosing a modelling strategy

The literature points to a wide range of potential models and estimators to forecast trade marking activity, such as survey based forecasting, time-series modelling (e.g., ARIMA) and vector auto regression. The estimation strategy pursued here has resulted from careful considerations of the properties of data and feasibility of the modelling.

Some modelling strategies, especially those emphasising firm-level drivers of trade marking activity, would require specific data collection and then compiling variables from the data. For example, the innovativeness of businesses is likely to drive trade marking but observing this aspect in readily available data is not possible. Forecasting approaches requiring this were not deemed feasible for this study.

Time-series modelling, such as ARIMA, was considered as a forecasting strategy. ARIMA models the development of a time-series, producing forecasts from patterns detected in its history. However, implementation of this is complex in the presence of panel data, and the panel aspect (different types of filers, who behave differently) of the data was deemed more important than the time-series aspect. Furthermore, ARIMA relies chiefly on trends and patterns over time, disregarding effects of other variables. These can be included in an amended model, such as those used in Gabaly and Hidalgo (2013). Including control variables was considered to be important, since they capture the economic forces underlying trade marking activity. While a pure ARIMA model was not considered to be appropriate, the model used here is partly inspired by it, as it estimates the dependent variable in first differences (the integration component) and uses lags of the dependent variable in some specifications (the autoregressive component).

Vector auto regression (VAR) modelling was also considered, both in a time-series and panel data specification. A VAR model estimates a system of equations, in which a set of variables are all interdependent. For example, it could be reasoned that trade mark filing, R&D expenditure and turnover all depend on and affect each other. Yet, it was discovered that these relationships, if they exist at all, are too weak to be estimated with confidence. Trade marking is a rare event for most businesses individually and, in the aggregate, is largely unaffected by short-term fluctuations in other business variables. Furthermore, this estimation strategy would not be feasible for non-corporate trade mark filers.

Table 5: Overview of control variables			
Variable	**Unit**	**Availability**	**Source**
Real GDP	£b, deflated	1946-2020	OBR
Investment	Chain linked volumes	1987-2020	OBR
Investment by sector	Index, 2005 = 100	1970-2015	KLEMS
EU dummy	Equal to 1 from 1997		
TM10 dummy	Equal to 1 from 2013		
Registered businesses w/o employees	Thousands	2000-2015	ONS
Unregistered businesses w/o employees	Thousands	2000-2015	ONS
Self-employment	Millions	1993-2015	ONS
Turnover	£10m	2005-2015	FAME
Employees	£10m	2005-2015	FAME
Land & buildings	£10m	2005-2015	FAME
Plant & vehicles	£10m	2005-2015	FAME
Intangible assets	£10m	2005-2015	FAME
Overseas turnover	£10m	2005-2015	FAME
Gross profit	£10m	2005-2015	FAME
R&D	£10m	2005-2015	FAME
Remuneration	£10m	2005-2015	FAME
Tangible assets	£10m	2005-2015	FAME
Capital expenditure	£10m	2005-2015	FAME

Estimation of owner-type panels

First, estimation results using panels on the level of owner types are presented. There are seven owner types: companies, individuals, foreign owners, educational institutions, public bodies, other institutions and a final “other” category. Additionally, the models distinguish between first-time and repeat filers, so that the panel’s cross-sections have 14 segments.

The advantage of panel data estimation is that unobserved characteristics of the different groups can be controlled for, as they are assumed to be constant over time. The estimation can then be undertaken using the fixed- or random-effects estimator. For each model specification, the appropriate estimator was chosen on an individual basis. More details on specification tests and the random- and fixed-effects estimators can be found in appendices 2 and 3.

Two model estimations are presented in Table 6. Both include the change in real GDP and the change in investment. In the second model, the lagged change in trade mark filings is used as a further control variable. Additionally, there are dummy variables for the introduction of the EU trade mark (equal to one from 1996) and the “TM10” programme (equal to one from 2013). Under this programme, the IPO facilitated online filings without representation. An additional dummy variable is set to one for the foreign owner type from the start of the EUTM, since these are likely to be most affected by the introduction of the EUTM. The data show a steep drop in filings from foreign owners from the mid-1990s, but a continuous trend for other filers. Similarly, an additional dummy is used for first-time filers in conjunction with the TM10 programme, since they are most likely to be encouraged to file by the new offering.

Both models estimate that trade mark filings move in the same direction as GDP and investment. While individually, both of these variables are not statistically significant at the five per cent confidence level, they jointly have a significant effect. The EU dummy does not have a marked effect on all trade mark filers, but it has a large negative effect on foreign filings. This is no surprise given the large drop in foreign filings seen in the graphs above.

The models were estimated using various combinations of lags of the numbers of filings as well as the other control variables. It was found that adding further lags did not improve the model fit or forecasting ability, which is expected given that the model is already estimated in differences. Both models were estimated using random- and fixed-effects, and pooled OLS. A comparison of specification test statistics can be found in appendix 2. Taking these test results into account, model 1 was estimated with random-effects, and model 2 with fixed-effects.

Table 6. Estimation of trade mark filings, filer-type panels

	Model 1 Owner types Random effects		**Model 2 Owner types Fixed effects**	
Δ Real GDP	0.99	(1.26)	**1.41**	**(1.26)**
Δ Investment	4.71	(3.17)	**3.88**	**(3.16)**
EU dummy	-15.70	(61.71)	**5.42**	**(62.80)**
EU dummy * foreign	-585.89***	(130.70)	**-668.07*** **	**(169.71)**
TM10 dummy	160.18	(143.07)	**151.85**	**(142.66)**
TM10 dummy * first	297.26	(198.14)	**223.20**	**(199.49)**
Δ Number of filings (t-1)			**0.12***	**(0.05)**
Constant	99.85	(71.47)	**77.90**	**(54.68)**
Within R2	0.10		**0.12**	
Between R2	0.11		**0.18**	
Overall R2	0.09		**0.11**	
RMSE	509.29		**504.59**	
Breusch-Pagan LM	37.65***		**736.0*** **	
Pesaran	12.35***		**12.76*** **	
Serial correlation	0		**0**	
Hausman	4.97			
Number of observations	378		**378**	
Number of groups	14		**14**	

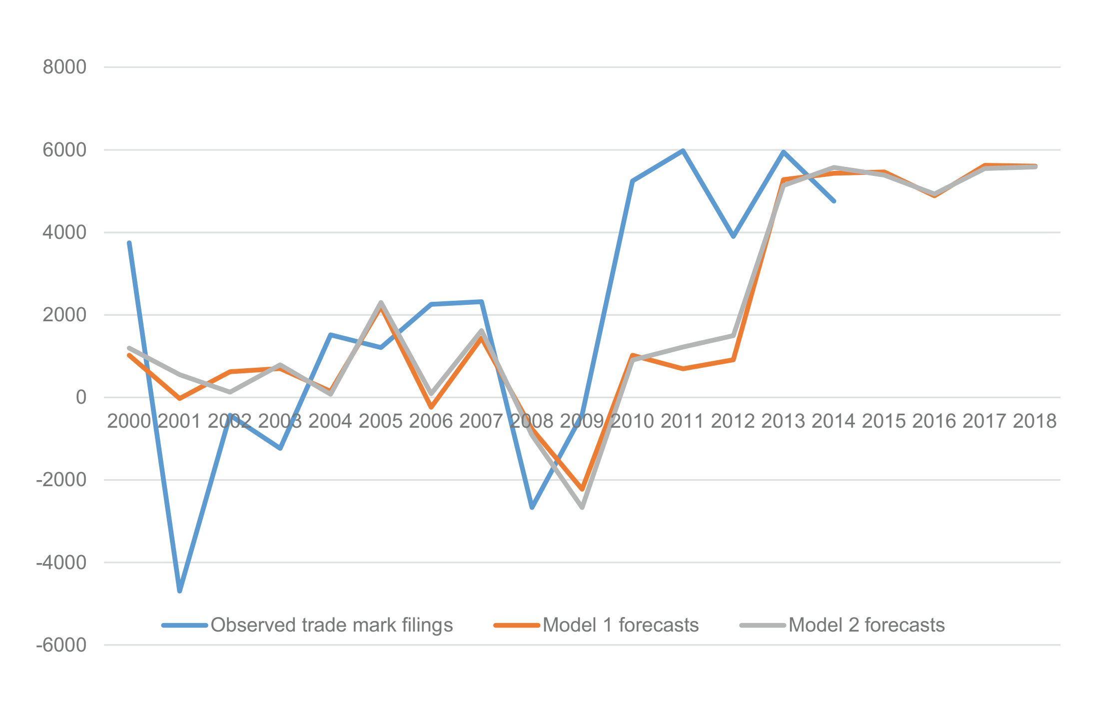
Note: Dependent variable: change in trade mark filings. Breusch-Pagan LM, Pesaran, Serial correlation and Hausman give the test statistics of the respective specification tests. Details on these tests can be found in appendix 2. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

The estimated effect of the trade mark programme is positive for both overall filings and first-time filings. While neither effect is statistically different from zero, the joint effect is significant and positive in both models. However, some caution is warranted when interpreting this parameter. First, the TM10 programme was only introduced in 2013, so that it only affected the last two years for which data are available. Second, it is possible that the introduction coincided with some other, earlier driver as the sharp increase of filings being picked up had already started from around 2011. Attribution of this rise to TM10 therefore is contestable.

The models are similar in terms of model fit. The R-squared, a measure of the proportion of the variation in the data that can be explained by a model, are slightly higher for the second model. Other specification test statistics, discussed in more detail in appendix 2 confirm model 2 as the preferred model. Forecasts based on model 2 require estimates of the number of filings for each additional period that needs to be estimated in the future, introducing additional uncertainty. For example, to forecast the filings for 2016, an estimate must be made for 2015 first, since this data is not yet available. Then, the next forecast for 2017 can be generated, and so on.

A further test of the models' fit is a comparison of predicted values against observed data. Figure 6 shows the observed yearly changes in trade mark filings as well as predictions from models 1 and 2 for the period 2000-2018. Both models follow the trends in the data well, but capture the rapid increase in filings only with a lag.

Figure 6: Forecasts using models estimated from owner type panels



Estimation of industry panels

Companies are the largest single group of filers; they also account for the bulk of the increase in filings. Some of the models looked at this in more detail. Having linked trade mark owners to company records, they can be segmented by industry. Specifically, 21 letter-code SIC groups are used. Additionally, the groupings by owner type (individual, foreign, etc.) are retained for trade mark owners not associated with an SIC code. Investment data are available by industry; all other variables are used at the macroeconomic level. However, the estimation strategy allows for different intercepts of the model, i.e., different levels of change in filings by group.

The estimation results for two models are presented in Table 7. Since all control variables – except for real GDP – are only available up until 2015, they have been included with a lag to facilitate forecasting. Recognising that trade mark filings could be driven by start-ups and self-employment, model 3 contains a range of measures of firm demographics. These are the change in the number of registered and unregistered businesses with no employees, and the change in the number of self-employed people. These try to capture the activity of micro-businesses and start-ups, which could explain the rapid increase in filings from first-time filers.

Table 7. Estimation of trade mark filings, industry panels

	Model 3 Industry level Fixed effects		Model 4 Industry level Fixed effects	
Δ Real GDP			0.52*	(0.22)
Δ Investment (t-1)			-0.57	(0.55)
EU dummy			0.74	(13.35)
EU dummy * foreign			-283.67***	(50.28)
TM10 dummy	76.06**	(27.50)	43.29	(29.87)
TM10 dummy * first	49.44	(35.41)	48.01	(41.49)
Δ Number of filings (t-1)			0.13***	(0.03)
Δ Regis'd businesses w/o employees (t-1)	-2.00***	(0.47)		
Δ Unreg'd businesses w/o employees (t-1)	0.23*	(0.09)		
Δ Self-employment (t-1)	-290.55*	(139.25)		
Constant	37.22**	(13.02)	16.66	(11.59)
Within R2	0.06		0.07	
Between R2	0.08		0.17	
Overall R2	0.05		0.06	
RMSE	172.36		210.48	
Pesaran	35.72***		40.83***	
Serial correlation	1.68		1.68	
Hausman	57.75***			
Number of observations	728		1456	
Number of groups	56		56	

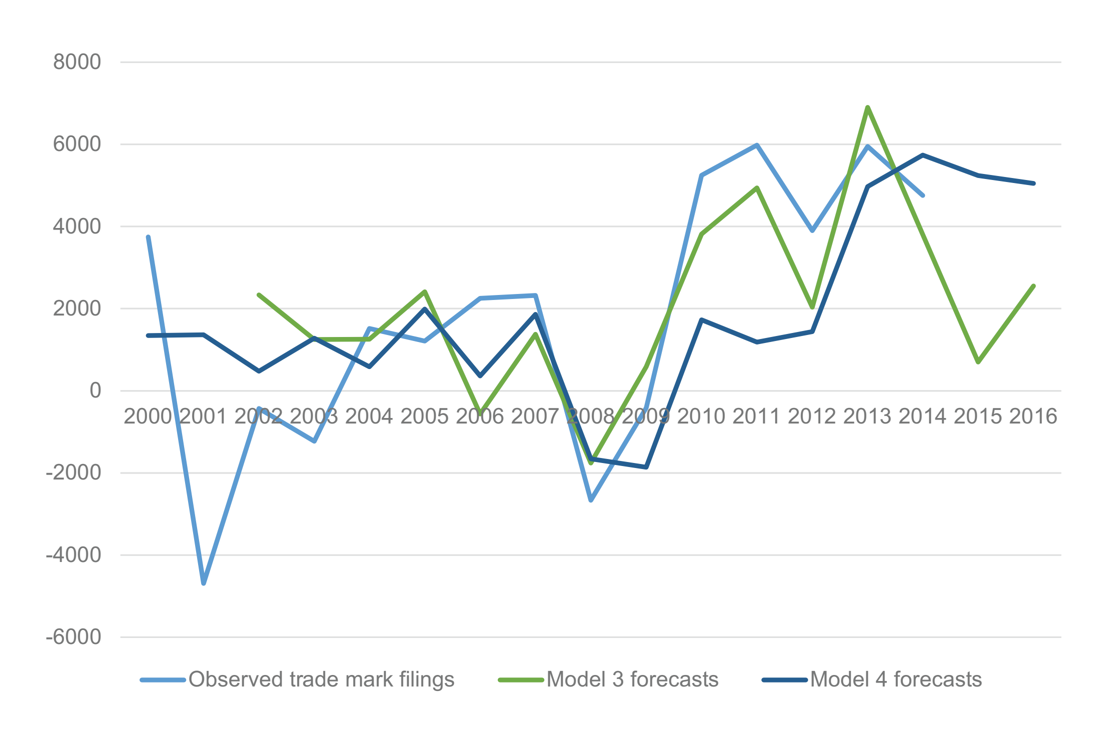
Note: Dependent variable: change in trade mark filings. Breusch-Pagan LM, Pesaran, Serial correlation and Hausman give the test statistics of the respective specification tests. Details on these tests can be found in appendix 2. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Surprisingly, only the change in the number of unregistered businesses that do not have employees has a positive effect on filings; the other business variables have negative effects. However, the large negative effect of self-employment should not be over-interpreted, since this variable is measured in millions.

The dummy variables have the same effect as before: the TM10 variable has a positive effect. The EU dummies could not be used since the other control variables are only available from 2000, and the time before the introduction of the EU trade mark is therefore not captured.

Model 4 uses variables like those used in the first set of estimations. However, the investment variable used here measures investment by industry. These variables have the additional advantage that they are available for longer time-series. The investment data by industry are only available up until 2014, so that the variable is used with a lag, for forecasting purposes.

Figure 7: Forecasts using models estimated from industry panels



As before, GDP has a positive impact on filings. The impact of investment is estimated to be slightly negative, but is individually not statistically significant. The coefficients of the dummy variables are also stable: negative for foreign companies for the EU dummy, and positive for the TM10 dummy. The coefficients are smaller in magnitude, because the data are sliced up more finely, and each one of them is therefore smaller.

Because of the different time horizons used for estimations, it is not meaningful to compare the models in terms of their R2s or RMSE. A look at Figure 7 reveals that the predictive ability of model 3 is more accurate than that of model 4. Model 3 follows the observed values closely and can predict the increase in filings from 2010/2011. For 2015, the model predicts a stagnation or slight drop in the change in the number of filings. This is driven by the stagnation in self-employment seen in 2014 and 2015. For 2016, the model predicts another increase.

Estimations with firm level micro-data

For the largest trade mark filers, owners have been linked to company information from Bureau van Dyke's FAME database. This holds data from financial reports. Just short of 600 trade mark owners have been augmented with data on assets, investment and financial performance. These have been aggregated again by letter SIC code. Data are available for the past ten years.

Table 8 gives the correlation matrix of the number of filings with these variables. As expected, most of these correlations are positive, but quite small. Notice that these are correlations on the aggregated level, and company variables have been summed across observations to capture differences in sizes of different industries.

Table 9 gives estimation results with different combinations of control variables. Since data are only available until 2015, all are entered with a lag to enable forecasting. In both models, none of the variables has an effect that is statistically different from zero. Therefore, models using panels based on firm level data are not further considered for forecasting. A number of alternative model specifications were undertaken using firm-level microdata from FAME. In addition, the alternative ONS Virtual Microdata Lab business data was tested, which had a larger sample size. However, the results of models were very poor, suggesting that the drivers for firm-level trade marking is far more complex than that may be represented using standard business data. One alternative explanation for this result might be that the time-series are too short to produce satisfactory models. At the firm level, there is also a small number of large filers. The number of firms going into each panel is relatively small, so that these are dominated by one or two large firms.

Table 8: Correlation of trade marks with company data

	Correlation with number of TM filings		Correlation with number of TM filings
Turnover	0.015	Gross profit	0.025
Employees	0.013	R&D	0.012
Land & buildings	0.014	Remuneration	0.006
Plant & vehicles	0.021	Tangible assets	0.009
Intangible assets	-0.001	Capital expenditure	0.000
Overseas turnover	0.025		

Note: The numbers presented are simple correlations of the number of filings with other variables in levels without additional controls.

Table 9: Estimation of trade mark filings using quasi panel from company data				
	Model 5 Industry Level		**Model 6 Industry Level**	
	est	s.d.	est	s.d.
Δ Plant & vehicles (t-1)	-34.12	(-247.5)	-41.33	(-247)
Δ Overseas turnover (t-1)	64.65	(-164.7)	63.52	(-164.2)
Δ Gross profit (t-1)	-44.75	(-116.0)	-38.59	(-115.7)
TM10 dummy			30.23	(-36.2)
TM10 dummy * first			88.5	(-49.8)
Constant	27.25***	(-6.7)	21.8**	(-6.9)
Within R2	0		0.01	
Between R2	0		0	
Overall R2	0		0.01	
RMSE	261.34		260.52	
Number of observations	1535		1535	
Number of groups	55		55	

Note: Estimated with random-effects. Dependent variable: change in trade mark filings.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses.

Forecasting trade mark filings

To forecast the number of filings, the predicted changes have to be applied to the last observable data point. From the estimations above, model 2 estimated for owner types using a lagged dependent variable has emerged as the preferred specification. Forecasts from all models are presented in Table 10. To produce forecasts for 2017 and 2018, the predicted changes for the previous year re-enter the model for the following year where this is required.

Table 10. Forecasts of trade mark filings

	Model 1 Owner types	Model 2 Owner types	Model 3 Industry level	Model 4 Industry level
2014 (observed)	50931	**50931**	50931	50931
2015	56394	**56319**	51629	56173
2016	61276	**61248**	54179	61223
2017	66901	**66793**	56729	66272
2018	72505	**72380**		
Fiscal years				
2014/15 (observed)	50268	**50268**	50268	50268
2015/16	57614	**57551**	52267	57436
2016/17	62682	**62634**	54817	62485
2017/18	68302	**68190**	42547	49704
2018/19				
Variables				
Δ Real GDP	x	**x**		x
Δ Investment	x	**x**		x (lagged)
EU dummy	x	**x**		x
EU dummy * foreign	x	**x**		x
TM10 dummy	x	**x**	x	x
TM10 dummy * first	x	**x**	x	x
Δ Number of filings		**x (lagged)**		x (lagged)
Δ Regis'd businesses w/o employees			x (lagged)	
Δ Unregis'd businesses w/o employees			x (lagged)	
Δ Self-employment			x (lagged)	

The models based on owner types predict further steady increases in the number of trade marks. The increases predicted by the models on industry level are smaller, largely due to the slow-down in the growth of self-employment observed for 2015.

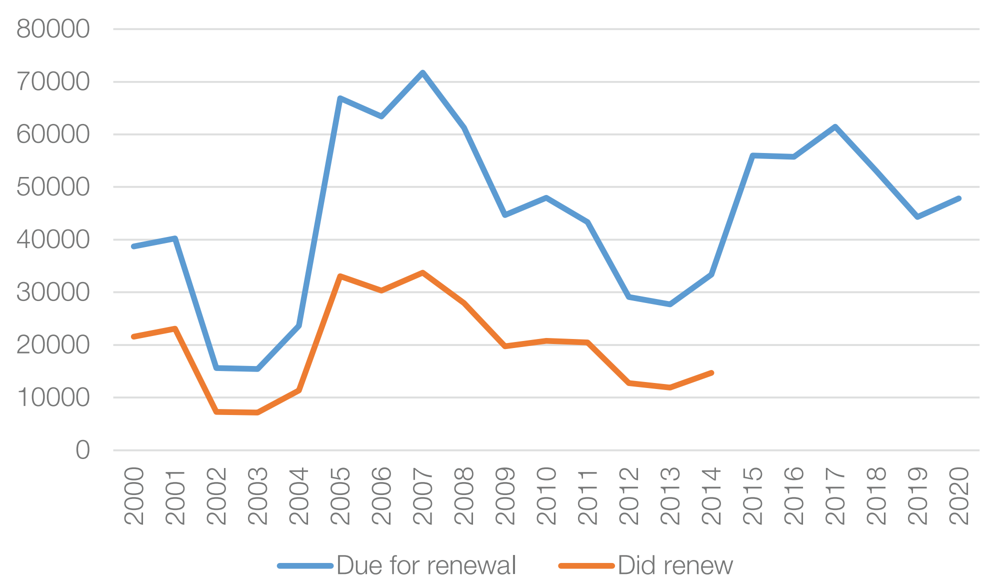
Forecasts are provided both for calendar and fiscal years. The fiscal year runs from April to March. The transformation from calendar to fiscal years was conducted on a proportional basis, meaning that three-quarters of the trade mark filings predicted for year t were added to one quarter of trade mark filings predicted for year t+1 to arrive at the predicted filings for fiscal year t/t+1. This method was chosen because control variables used were on a calendar-year basis, and quarterly modelling would have inevitably been more complicated due to cyclical trends.

Forecasting renewals

Next to registering new trade marks, it is also the task of the IPO to process renewals. A trade mark that is filed today must be renewed every ten years. However, not all trade marks that are due to re-register are renewed. Therefore, renewals must be forecast as well.

Figure 8 gives the number of trade marks that are due to be renewed and that are renewed each year since 2000. Because most trade marks that expired before 2003 have been removed from the database, the analysis of renewals will only consider the period after 2003. Renewal dates are modelled using the filing data. Starting from the filing date, all future renewal dates are computed using information about the length of time trade marks last. The database includes when a trade mark expired or is due to expire, so all the renewals from registration can be modelled. Some imprecision is introduced as trade marks can be renewed six months before they are due for renewal and early renewal does sometimes occur. However, the scale of this is modest and so should not affect results overall.

Figure 8: UK domestic trade marks due for renewal and actually renewed



Each year, about half of trade marks due to be re-registered are in fact renewed. The bump from 2005 to 2008 can be explained by the change in the re-registration horizon. Before 1995, a trade mark was first due to be renewed after seven years, and every fourteen years thereafter. Since 1995, trade marks should be renewed every ten years. This results in a cyclical pattern of drops and increases in trade marks that come due for renewal (details about how this effect comes about are provided in appendix A4).

To forecast renewals, data have been aggregated into quasi-panels of the number of renewals by owner types. These have been augmented by the same macroeconomic variables as previously used in the estimations of new filings. The strongest predictor of actual renewals is the number of trade marks due for renewal. However, investment and several variables on business demographics show significant effects as well.

Table 11: Estimation of UK domestic trade mark renewals

	Model R1 Owner Types (preferred model)		**Model R2 Owner Types**		**Model R3 Owner Types**	
	est	**s.d.**	est	s.d.	est	s.d.
Δ Total due for renewal	**0.51*** **	**(0.01)**			0.51***	(0.01)
Δ Investment	**-0.32**	**(2.20)**			0.31	(2.33)
Δ Due for 1st - 10th renewal			included			
Δ No. businesses					951.05	(508.08)
Δ No. employers					-951.57	(507.46)
Δ No. unregistered business, no employees					-950.66	(507.91)
Δ No. registered business, no employees					-953.06	(509.43)
Constant	**-19.29**	**(25.73)**	37.99	(21.12)	-36.75	(48.05)
Within R2	**0.99**		1.00		0.99	
Between R2	**0.95**		0.67		0.95	
Overall R2	**0.99**		0.99		0.99	
RMSE	**221.51**		157.32		218.35	
Breusch-Pagan LM	**31.88***		23.09		2.75**	
Pesaran	**2.89***		0.27		2.75**	
Serial correlation	**0.06**		10.63*		25.65***	
Hausman	**7.12***					
Number of observations	**77**		**77**		**77**	
Number of groups	**7**		**7**		**7**	

Note: Estimated with fixed-effects. Dependent variable: change in trade mark filings. Breusch-Pagan LM, Pesaran, Serial correlation and Hausman give the test statistics of the respective specification tests. Details on these tests can be found in appendix 2. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 11 shows three model estimations, all with the change in trade marks renewed as the dependent variable. All of them exhibit a good fit to the data, as shown by the high overall R2s. Model R1 is the most basic specification, including only the change in trade marks due for renewal and the change in aggregate investment. As could already be seen from Figure 8, about half of trade marks due for renewal are in fact renewed, corresponding to a coefficient for that variable of 0.51. Renewals correlate negatively with investment, but this effect is insignificant. Real GDP does not have a significant effect on renewals.

In model R2, trade marks are considered separately by the round of renewals they were due for, i.e., the number of trade marks due for renewal for the first time, second time, etc. are all allowed to have separate effects. This addresses the fact that a recently filed mark is more likely to still be relevant to a firm, and therefore more likely to be renewed. Including these more detailed due-to-renew data has such a strong effect that none of the other variables remained significant.

Model R3 is an extension of model R1 in that the changes in the numbers of businesses, employers, unregistered and registered businesses without employers were included alongside investment. The number of businesses has a positive effect on renewals. This might be the case because trade mark owners feel fiercer competition and IP is therefore more valuable to them. The number of employers, registered and unregistered businesses without employees, however, have negative effects.

From all three models, it can be concluded that the best predictor of the number of trade marks renewed each year is the number due for renewal. The fraction of trade marks that are in fact renewed has changed little over time, and has not been affected by the change in the renewal horizon. This is a welcome result, since it gives the IPO a good prediction of the number of renewals to be expected in a year. However, over the coming years, substantial volatility in the number of renewals can be expected, as a legacy of the change in the renewal regime. Yet, information on the number due to be renewed in the future can easily be drawn from the trade marks register.

Figure 9: Predicted change in UK domestic trade mark renewals

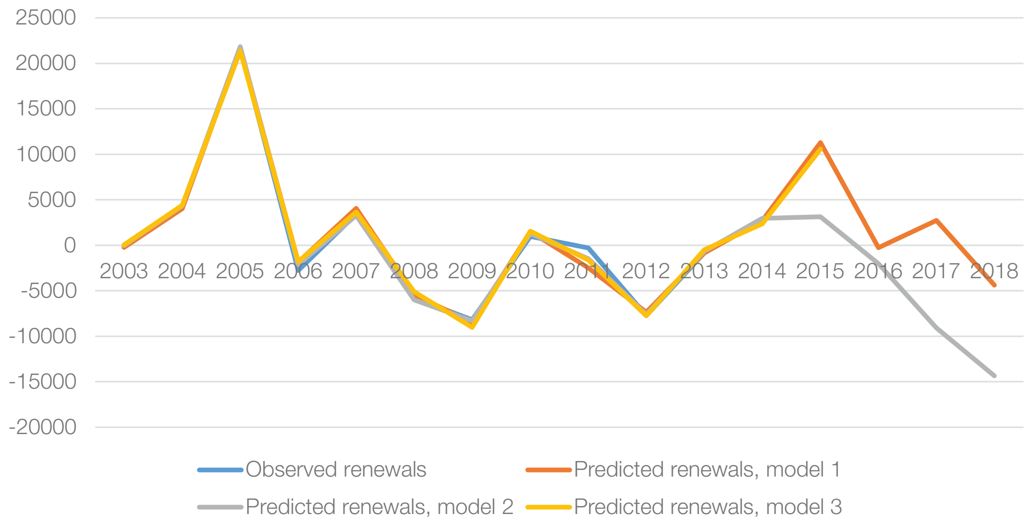


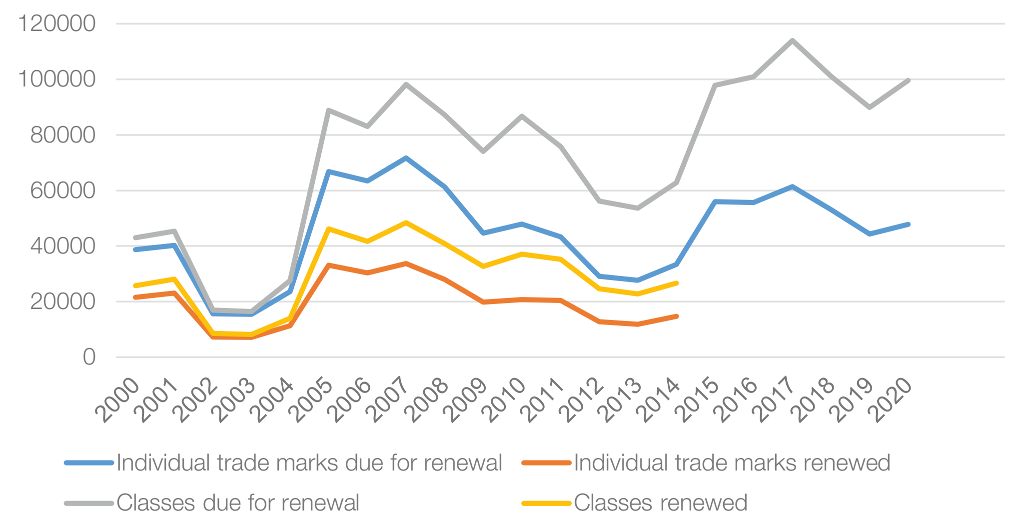
Figure 9 plots the predicted changes in renewals against the observed values. Predictions from all models are very similar and track the observed change in renewals closely up until 2014. All models predict a large increase in the number of renewals for 2015 and small increases or a slight decrease thereafter. Models R1 and R2 have the advantage that all variables are available at least until 2020. The business demographics variables used in model R3 on the other hand are only available until 2015.

Forecasting the number of classes renewed

Trade marks are filed for different classes (45 in total, 34 for goods and 11 for services). When renewing a trade mark, the owner can choose which classes to renew. Therefore, it is also of interest for an IPO to know the classes that are being renewed. Unfortunately, the database holds only those classes a trade mark was registered for at the date of the snapshot or when it expired. If an owner chose not to renew a certain class over the lifetime of the trade mark, this will not appear in the data.

Figure 10 contrasts the number of individual trade marks and classes renewed and due for renewal. Trade marks are filed on average in 1.7 classes, and the number of trade marks due for renewal is correspondingly higher. Individual trade marks and classes renewed follow roughly parallel paths, implying that the number of classes registered does not influence the propensity to renew.

Figure 10: Individual trade marks and classes renewed and due for renewal



The same models used to forecast individual trade mark renewals are also estimated for renewed classes. Reassuringly, the coefficients presented in Table 12 do not differ significantly from those seen in Table 11. The coefficients on the number due for renewal remain constant at 0.6, and the coefficients on investment are roughly twice those estimated earlier, corresponding to an average of approximately two classes per trade mark.

Table 12: Estimation of trade mark classes renewed						
	Model RC1 Owner Types (preferred model)		**Model RC2 Owner Types**		**Model RC3 Owner Types**	
	est	**s.d.**	est	s.d.	est	s.d.
Δ Total due for renewal	**0.51*** **	**(0.01)**			0.52***	(0.01)
Δ Investment	**5.26**	**(4.63)**			6.22	(4.96)
Δ Due for 1st - 10th renewal			included			
Δ No. businesses					1760.51	(1098.75)
Δ No. employers					-1761.92	(1097.42)
Δ No. unregistered business, no employees					-1759.61	(1098.39)
Δ No. registered business, no employees					-1763.27	(1101.65)
Constant	**-82.41**	**(54.75)**	-55.21	(53.52)	-144.78	(103.74)
Within R2	**0.98**		0.98		0.98	
Between R2	**0.98**		0.99		0.98	
Overall R2	**0.98**		0.98		0.98	
RMSE	**470.84**		416.87		467.56	
Breusch-Pagan LM						
Pesaran						
Serial correlation						
Hausman						
Number of observations	**77**		77		77	
Number of groups	**7**		7		7	

Note: Estimated with fixed-effects. Dependent variable: change in trade mark filings. Breusch-Pagan LM, Pesaran, Serial correlation and Hausman give the test statistics of the respective specification tests. Details on these tests can be found in appendix 2. Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Forecasts of the levels of renewals are presented in Table 13 for both individual trade marks and classes renewed. All models predict a large increase in renewals in 2015 and a stable level thereafter until 2018. The forecasts based on model R1 are slightly higher than those generated by model R2, reflecting the expected increase in investment. For model 3, expected changes after 2014 had to be extrapolated because no data are available to generate forecasts beyond 2015. Therefore, this result should be treated with caution.

Table 13: Forecasts of UK domestic trade mark renewals

	Individual marks			Classes		
	Model R1 (preferred)	Model R2	Model R3	**Model RC1 (preferred)**	Model RC2	Model RC3
2014 (observed)	**14697**	14697	14697	**26666**	26666	26666
2015	**25998**	17833	25273	**44394**	29533	43195
2016	**25730**	15806	35849	**45472**	12712	59724
2017	**28471**	6734	46425	**52023**	9600	76253
2018	**24073**	-7630		**45189**	-39959	
			Fiscal years			
2014/15 (observed)	**14506**	14506	14506	**26319**	26319	26319
2015/16	**25931**	17326	27917	**44663**	25328	47327
2016/17	**26415**	13538	38493	**47110**	11934	63856
2017/18	**27372**	3143	34818	**50315**	-2789	57190
2018/19						
Variables						
Δ Total due for renewal	**x**		x	**x**		x
Δ Investment	**x**		x	**x**		x
Δ Due for 1st - 10th renewal		x			x	
Δ No. businesses			x			x
Δ No. employers			x			x
Δ Unregis'd businesses w/o employees			x			x
Δ Regis'd businesses w/o employees			x			x

5. Discussion and Policy Outlook

The previous chapter has described the findings to support IPO in its operational work. This chapter looks at the evidence on two policy areas. Firstly, the adoption of the EUTM in the 1990s and its impact on UK IPO filings provides evidence about the use of the Europe-wide mark. It indicates that the introduction was associated with a reduction of the growth rate of trade mark filings in the UK each year by around 1,500. A second policy driver is the extent to which recent simplification of the application process has encouraged trade marking. The evidence here is mixed as it is difficult to distinguish the effects of IPO policy from other drivers.

Since the UK referendum to leave the European Union, there is interest in forecasting the likely effect of different models of trade mark co-ordination between the UK and the EU. The chapter also looks at whether particular IPO policies can be forecast using the modelling here. The chapter ends on some of the possible next steps in this area of work, noting the context of the current study.

Effect of the introduction of the EU trade mark

In 1996, the European Union-wide Community Trade Mark was introduced allowing filers to receive a trade mark valid across the single market. The EU Trade Mark (EUTM) – as renamed in March 2016 – is valid in the UK. The introduction meant that businesses and individuals could register a mark at the European Office for the Harmonization of the Internal Market (now the EU IPO) and many businesses, especially those from outside the UK, began to use the service instead of registering in the UK.

Table 14: Estimates of the effect of the EU trade mark

	On UK applications		**On foreign owners**	
	Marginal effect	Cumulative 1996-2014	Marginal effect	Cumulative 1996-2014
Model 1, owner-type panels	-219.8	-3956.4	-1171.78	-21092.04
Model 2, owner-type panels	-544.04	-9792.72	-598.5	-10773
Model 2, industry level panels	-538.72	-9696.96	-448.52	-8073.36

Note: Effect on the total number of trade marks computed as coefficient * number of groups.

From the regression analysis, the extent of this shift in the 1990s is discernible, though there is a mixed picture provided by the different models. Table 14 indicates the average number of trade marks that would have been registered additionally in the UK had the EUTM not been available. The table gives the marginal as well as cumulative effect on total UK applications as well as on foreign owners filing in the UK. The marginal effect is the reduction on the annual change in filings.

Adding these annual reductions or increases over the years between 1996 and 2014, the effects become sizable. It is estimated that filings from foreign owners in 2014 were reduced by between 8,000 and 21,000 due to the EUTM. The effect on total filings is also estimated to be negative but smaller. This might reflect an overall positive trend in the data. Estimates are derived by multiplying the number of segments by the estimated coefficient on the EU dummy for total UK applications and applications from foreign owners only.

Since the UK referendum to leave the European Union, there is interest in forecasting the likely effect of different models of trade mark co-ordination between the UK and the EU. The previous paragraphs estimate the number of trade marks that are registered in EU IPO that would have registered in the UK had EUTM not been developed. The cumulative estimate would represent trade marks on the EU register that may need the IP protection that they currently have in the UK were policy to return to the pre-EUTM position. However, because trade marking has seen such strong growth in the past decades, it is likely that this is an under-estimate.

A second aspect to consider is the annual additional new applications that might arise. Overall, there were 108,000 direct filings for trade marks at the EU IPO in 2015. For those trade mark owners who also require IP protection in the UK, it could become necessary to file for a separate trade mark in the UK.

It is probable that only a portion of the filings at EU IPO would also consider a UK filing after any change in the UK's position. An indication of the lower bound for the EU IPO marks that may require a UK registration is the 12,524 direct filings from the UK at the EU IPO in 2015 (Statistics of European Union Trade Marks, 2016). If all of these were to additionally file for protection in the UK, should the EUTM no longer cover the UK, this would represent an additional increase in filings of 20 per cent (based on estimated UK domestic filings in 2016 of 61,211). Further, it is far larger than the marginal estimate given in Table 14, suggesting that the forecast modelling based on filings at the time when the EU trade mark was introduced, and overall filings were much lower, may underestimate the effect of the EU trade mark. However, it is likely that some of these filers explicitly sought to protect their IP in the European Union, because they do not require protection in the UK.

Policies to simplify trade mark application process

One of the notable features in recent years has been the steep rise in the number of small businesses that have sought trade mark protection for the first time. The IPO has also set in place measures to simplify the application and so reduce the cost of registering a mark. The opportunities have been taken by individual small businesses and individuals and by intermediaries seeking to support businesses to register their trade marks.

Estimating any impact of specific IPO policies has proved difficult, primarily because it is difficult to separate what has driven the recent rise of trade marking. It seems likely that the cost of trade marking has been reduced because of process changes, marketing of the ease and value of a mark and the introduction of registration services online. Equally, however, the UK economy has seen a large growth in the number of start-ups and SMEs, alongside a rise in self-employment. The evidence in this report suggests that new filers have been a significant driver of the recent growth of trade marks.

For estimation, the problem is that both sets of drivers have occurred at around the same time. The improvements in supplying the marks occurs at about the same time as the increased numbers of new businesses. The forecasting has found it difficult to discern the different drivers separately and it is very likely that both have been important.

Trade mark forecasting context and next steps

Forecasting the likely future level of trade mark applications is important for IPO to plan resources. This work has developed current modelling approaches to improve such forecasts. The most recent similar work on trade marking – the EU IPO has commissioned a forecasting model for trade marks (Hidalgo & Gabaly, 2012, 2013) – was discussed earlier in the report. These studies firstly sought to model trade marking purely using register information and at quite an aggregate level. In Hidalgo and Gabaly (2013), macroeconomic variables were added.

There are three main differences between the approach used in these studies from the current work. First, this work splits trade mark filers into different segments, whereas Hidalgo and Gabaly looked at trade mark filings in the aggregate. This allows data about the different segments to be integrated into the modelling. Second, the EU IPO studies estimated the level of trade mark filings, while here the change in filings is estimated. Both changes appear to improve the modelling. Further, the modelling here has been underpinned by a significant improvement to the underlying datasets, linking the owner of a trade mark to data about the type of owner.

This linking exercise is a resource intensive exercise. It produces additional variables to model trade marking activity, by identifying characteristics of the trade mark owner from business databases. Some of the additional variables – such as owner type – prove useful in segmenting the modelling. However, it is apparent that the variables derived using business characteristics do not greatly improve the forecasts. The preferred models are mainly auto-regressive with policy dummies.

Continuing to use simple, time-series approaches would therefore be justified for activity modelling to support the resource planning of the IPO. However, one of the key dimensions for future work is to be able to represent policy and intellectual property related policy specifically in the models. Such interventions are occurring at sector and business type level, so the sophistication of the underlying datasets used in this study may be warranted if these interventions shape the future registration of trade marks.

An area of the modelling that may need developing is the representation of the various international routes to co-ordinate the trade mark application. This work has focused on the UK register and applications and renewals to that register. The modelling here does begin to lay the groundwork for going further. Where an entity is the owners of several UK trade marks, this is now represented in the data. It then makes it possible to link across different registers by the owner.

Appendix A1: Data linking

The register of trade marks up until January 2015 is publicly available from the IPO. Information on trade mark owners is limited to their name and address. Since many owners are companies, the register was linked to the Companies House database to extract further information. Since Companies House numbers were not provided, matching had to be based on names and was conducted in several steps.

Matching strategy

Trade marks are filed by individuals, institutions such as universities, museums and charities, and companies. Companies register most trade marks, and they are also the group to which official microdata can be linked at the firm level. To make use of information from official sources, applicants first have to be matched to the Companies House register to retrieve their registration number. Due to differences in spelling and recording errors, this is not always straightforward. Furthermore, foreign companies, individuals and entities that have not registered as an entity covered by the Companies House register cannot be matched. To maximise matching success, data linking was conducted using the following steps.

1. **Standardise names**
   Even in administrative data, it is common to find different spellings for the name of the same company. For example, a limited company could legitimately state its name once ending with "Limited" and once using the abbreviation "Ltd.". To filter out these cases, an automated programme for name standardisation was employed. In the example above, both "Limited" and "Ltd." would be transformed into "LTD".

2. **Isolate companies**
   The name standardisation already finds the most common forms of company types, such as "LTD", "LLC" or "PLC". Since there are also international applicants in the database, names were searched for international company forms as well, such as "GMBH" or "NV". Furthermore, names were searched for common terms in the names of other institutions, such as "university", "museum", and their equivalents in other languages. While working with the data, the search strategy was continuously refined, adding more terms that are often found in company names, such as "consulting" or "management", but also "fashion", "media", etc. There is a risk that this identifies other organisations that are not companies, but the main goal was to isolate natural from legal persons, as individuals have the highest probability of yielding wrong matches. In total, the search was conducted using 130 terms. It was also assumed that all applicants whose names consisted of a single word could be classified as companies.

   Lastly, owner names were matched to a database of common – largely English-language – first and last names. This was successful in classifying a substantial number of applicants as individuals. The database of common names and surnames did not capture names originating from outside the UK. The database was amended with names from the patent register, which more clearly identifies individuals and therefore allowed enriching the names database with common names used in the UK but from languages other than English. Identifying individuals is important, because matching strategies to find companies on the register would otherwise give a very large number of false matches as it is common for a company to be named using a person's name.

3. **Perfect matching on name and postcode**
   After standardising the names on both the trade mark dataset and Companies House register extract, the first matching on both standardised name and postcode was performed for those applicants not identified as an individual. Matching on postcode as well as name gives some assurance that the right company is actually captured, since name standardisation may increase the risk of "false positives", i.e., two records being matched that are in fact not the same company. This is less likely where both names and postcode are exactly the same.

4. **Perfect matching on name**
   Matching on postcode bears the risk that those companies who have moved their office since registering their trade mark or register trade marks to premises different from the company registration will not be captured. Even though IPO asks trade mark owners for yearly updates, not all respond, and some become untraceable. Therefore, proceeding from step three, unmatched records previously identified as companies were matched based only on name.

5. **Matching with OpenRefine**
   OpenRefine (formerly Google Refine) is an online service that performs matching. To match company names, it uses the OpenCorporates.com database. The disadvantage of this process is that it is less transparent, and the basis of matching remains somewhat in a black box. Therefore, this was used only to match UK companies that had not been matched in steps 3 and 4. The algorithm judges similarity between names, and also takes into account the post code. It outputs the closest match to each record together with a similarity score. After some quality assurance, all matches but those with the lowest scores were accepted. As a means of quality assurance after steps 3 to 5, all those companies and trade mark owners were unmatched, where the date of the last filing for a trade mark preceded the incorporation date of the company. Using the last filed date is sensible in this respect, because many, especially large companies often re-incorporate. Using the last date assures that most of these matches are not lost.

6. **Clerical matching**
   Those UK trade mark owners holding more than 50 marks were matched clerically, to make sure the most active applicants are covered. Often, it was possible to identify the Companies House number from directors' names or previous company names. In many instances, companies were dissolved before 2008 and had therefore not been matched. Those that were left unmatched are either other organisations or individuals.

7. **Fuzzy matching**
   Matching trade marks to UK companies using "fuzzy matching" was considered as well. This technique recognises that records may contain typos or more severe deviations that cannot be captured by name standardisation alone. For example, "John William Smith

and Sons Limited" could have registered their patent as "J.W. Smith & Sons Ltd". Typos or abbreviations of names are hard to capture by standardisation. Fuzzy matching looks for commonalities in names and establishes a percentage value for the similarity between two records. Then, a cut-off value was determined. However, this method has not been used so far, as the initial work indicated a risk of false positives. This arises for two reasons. Firstly, the presence of spelling mistakes and typos, while common in surveys, is likely to be uncommon in an administrative dataset such as this. Secondly, and more likely, in the trade mark register will be unincorporated entities owning trade marks trading under names that are close to a company name. So, a "John William Smyth" may individually own a trade mark and fuzzy matching will then find the company with a similar name.

The final matching strategy results from several iterations, each matching followed by quality assurance and then refining the matching strategy. Insights from quality assurance led for example to the exclusion of individuals when matching only on name, and the dropping of matches where the incorporation date of the company fell after the last filing date for a trade mark. After these iterations, there is sufficient confidence that a robust matching strategy has been found.

To check the quality of the matching, random samples were drawn from the trade marks database following the implementation of different matching strategies. The sampling approach means that multiple trade mark owners occur multiple times and have therefore a higher chance of being drawn, which reflects that one would be more concerned about getting these right. Samples of matched companies were drawn to check whether the matches are right, and of unmatched companies, to see whether the matching strategy could have been improved.

In general, it was found that the number of false matches (false positives) is low. It was further lowered through iterations of the matching process. On the other hand, it was found that about half of unmatched trade mark owners can be matched clerically. However, it often takes substantial effort to do so. From the last iteration, no possibilities were found to lower the number of unmatched owners further.

Since companies were also matched on name only, some discrepancies in addresses were found. In those cases, some further checks that the match was right were conducted. A first check is that the company was incorporated before the trade mark was filed. Secondly, Companies House holds a filing history for most live companies, in which changes of address can be found. In all cases in the quality assurance sample, addresses could be reconciled in this way.

Among the unmatched trade mark owners, about half could be matched manually for both corporates and non-corporates. However, it often took considerable effort to find a match, which could not be automated, so this did not yield further improvements in matching strategy.

Data analysis

This analysis looks at unique owners of trade marks (unique in terms of name and postcode combinations). Table A1 sums up how these were classified and matched:

Table A1: Trade mark owners

	No of Entities
Unique owners	**390,614**
Identified as UK companies	171,761
Identified as UK individuals	73,668
Identified as other UK institutions	2,252
Unidentified UK owners	10,222
Foreign owners	132,711
Companies matched in total	**158,802**
Matched on name and postcode	55,092
Matched on name	59,327
Matched by OpenRefine	44,308
Matched manually	75

In total, there are 390,614 unique (in terms of name and postcode) owners of trade marks in the database. Roughly two-thirds of these have a GB address. Of these 247,681 British owners, 96 per cent were classified as either companies, individuals or other institutions, such as universities, museums or government organisations.

Overall, a match rate of 40.7 per cent was achieved. Among British companies, a match rate of 62.1 per cent was achieved. Moreover, there were around 50,000 matches for trade mark owners that were previously not identified as British corporates. Some of these were foreign owners that could be matched to a UK subsidiary. After the UK, most trade mark owners came from the US (22,613), Germany (8,858) and France (8,623).

The table above looked at trade mark owners. Among them, they owned 974,313 trade marks in total, with an average of 2.8 trade marks per owner.

Table A2: Owners of individual trade marks	
Total trade marks	974,313
Owned by UK companies	523,228
Owned by UK individuals	96,753
Owned by other UK institution	6,421
Owned by unidentified UK owners	14,970
Owned by foreign owners	332,941

Again, the split between domestically and foreign-held trade marks is roughly 2:1. However, among the British-owned trade marks, the weight is more on corporate owners, reflecting that companies are more likely than individuals and other owners to hold more than one trade mark.

Appendix A2: Specification tests and robustness checks

Unit root tests

An important assumption of OLS estimation with time-series data is that all series are stationary. To test this, unit-root tests have been performed. Table A3 shows the results of Fisher-type unit-root tests. This test is based on Dickey-Fuller tests for each panel unit. The null hypothesis of the test is that all panels contain unit roots, with the alternative that at least one panel is stationary. The Fisher specification of the test was chosen, because it can be used with unbalanced panels, which is the case here.

As the table shows, for both owner-type and industry level panels, the null hypothesis cannot be rejected, even when higher lags are included. Therefore, it has to be concluded that the time-series of the number of trade mark filings are non-stationary. OLS regressions of the series in levels would therefore not be valid, and any estimation should be based on differences instead.

Table A3: Unit root tests

	Trend	Drift	Test-type	Lags	P-value (levels)	P-value (differences)
New filings			Fisher	1	0.99	0
New filings		x	Fisher	2	0.36	0
New filings		x	Fisher	3	0.38	0
New filings			IPS	1	1	0
New filings	x		IPS	2	1	0
New filings	x		IPS	3	1	0.01
Real GDP			Fisher	1	1	0
Real GDP		x	Fisher	2	0.14	0
Real GDP		x	Fisher	3	0.27	0
Real GDP			IPS	1	0.99	0
Real GDP	x		IPS	2	0.16	0
Real GDP	x		IPS	3	0.03	0
Investment			Fisher	1	1	0
Investment		x	Fisher	2	0.07	0
Investment		x	Fisher	3	0.04	0
Investment			IPS	1	0.99	0
Investment	x		IPS	2	0.06	0.02
Investment	x		IPS	3	0.01	0

Table A3: Unit root tests

Note: Fisher-type tests are based on the Dickey-Fuller test. The Null-hypothesis of this test is that all panels contain unit roots, with the alternative that at least one panel is stationary. Im-Pesaran-Shin (IPS) tests have the same Null-hypothesis, but the alternative is that some panels are stationary. To use conventional estimation methods, the Null-hypotheses should be rejected with sufficient confidence, usually a P-value of the test statistic of less than 0.05. The P-values reported for the Fisher-type tests are based on the inverse chi-squared statistic.

Cointegration tests

Since there is evidence for unit roots in the data in levels, the series have also been tested for cointegration. Two series are considered to be cointegrated if both of them have unit roots, but a linear combination of them is stationary. To test for cointegration in panel data, the Westerlund error correction based test has been used. The test statistics presented in Table A4 give some evidence that the number of filings, real GDP and investment are in fact cointegrated, suggesting an error-correction model would be appropriate to model their relationship. However, it was found that this model had a poor fit and was not useful for forecasting.

Table A4: Cointegration tests

			P-values			
Lags	**Trend**	**Constant**	**Gt**	**Ga**	**Pt**	**Pa**
1			0	0	0.08	0.01
2	x	x	0.03	0	0	0
3	x	x	0.01	0	0	0

Table A4: Cointegration tests

Note: Based on a regression of the number of filings on real GDP and investment. The Null-hypothesis states that the series are not cointegrated.

Further specification tests

Some specification tests have been run for each model, and test results are presented in the tables throughout the text.

Table A5a: Specification tests for new filings models, owner-type panels

		Model 1			Model 2		
		RE	FE	Pooled OLS	RE	FE	Pooled OLS
Theil's U	Naïve model 1	0.402	0.401	0.42	0.413	0.39	0.413
	Naïve model 2	0.397	0.396	0.42	0.408	0.39	0.408
Breusch-Pagan LM	Chi-bar2	37.65	758.5		0	736.2	
	P-value	0	0		1	0	
Pesaran	Test statistic	12.35	12.44		12.64	12.76	
	P-value	0	0		0	0	
Serial	F-statistic	0	0		0	0	
	P-value	0.99	0.99		0.99	0.99	
Hausman	Chi2	4.97		1.58	29.52		0.0
	P-value	0.55		0.95	0.0		1

Table A5b: Specification tests for new filings models, industry-level panels

		Model 3			Model 4		
		RE	FE	Pooled OLS	RE	FE	Pooled OLS
Theil's U	Naïve model 1	0.49	0.49	0.53	0.6	0.6	0.6
	Naïve model 2	0.48	0.48	0.52	0.589	0.585	0.589
Breusch-Pagan LM	Chi-bar2	35.27					
	P-value	0.0					
Pesaran	Test statistic	35.27	35.72		40.23	40.83	
	P-value	0	0		0	0	
Serial	F-statistic	1.68	1.68		1.68	1.68	
	P-value	0.2	0.2		0.2	0.2	
Hausman	Chi2	73.02	57.75		34.45		
	P-value	0	0		0		

Table A5c: Specification tests for renewals models

		Model 1			Model 2			Model 3		
		RE	FE	Pooled OLS	RE	FE	Pooled OLS	RE	FE	Pooled OLS
Theil's U	Naïve model	0.103	0.106	0.103	0.08	0.075	0.08	0.102	0.104	0.102
Breusch-Pagan LM	Chi-bar2	0.0	31.88		0.0	23.09		0.0	2.75	
	P-value	1.0	0.06		1.0	0.34		1.0	0.01	
Pesaran	Test statistic	2.624	2.89		1.02	0.27		2.75	2.75	
	P-value	0.01	0.06		0.31	0.79		0.01	0.01	
Serial	F-statistic	0.06	0.06		10.63	10.63		25.65	25.65	
	P-value	0.81	0.81		0.02	0.02		0.0	0.0	
Hausman	Chi2	7.61	7.12	7.23	211.83			24.19		
	P-value	0.02	0.03	0.03	0.0			0.0		

Table A5d: Specification tests for renewed classes estimations

		Model 1			Model 2			Model 3		
		RE	FE	Pooled OLS	RE	FE	Pooled OLS	RE	FE	Pooled OLS
Theil's U	Naïve model	0.222	0.22	0.22	0.19	0.199	0.193	0.22	0.223	0.22
Breusch-Pagan LM	Chi-bar2	0.0	36.2		0.0	31.21		0.0	62.36	
	P-value	1.0	0.02		1.0	0.07		1.0	0.0	
Pesaran	Test statistic	1.99	1.78		0.0	0.03		2.22	2.183	
	P-value	0.05	0.08		0.99	0.98		0.03	0.03	
Serial	F-statistic	75.96	75.96		107.38	107.38		20.28	20.28	
	P-value	0.0	0.0		0.0	0.0		0.0	0.0	
Hausman	Chi2				68.25			4.02	4.13	3.76
	P-value				0.0			0.54	0.53	0.58

In the following, these methods are summarised:

Theil's U:
The Theil's U statistic compares the root mean squared error (RMSE) of a forecasting model to that of a naïve model. If Theil's U is larger than 1, this means the forecasting model is no better than guessing. For the models of new filings, two naïve models have been used: One based on a linear time trend, and one only on last year's filings. For renewals, last year's filings have been used as the regressor in the naïve model.

Breusch-Pagan Lagrange multiplier (LM) test
The Breusch-Pagan Lagrange multiplier test assesses whether it is necessary to run a panel data model or whether pooled OLS regression would be sufficient. The Null-hypothesis of the test is that there are no significant differences between panel units, so that the variance across them is zero. If the Null-hypothesis is rejected (i.e., a P-value of less than 0.05), this confirms that a panel data model (with random-effects) is the appropriate specification.

Pesaran cross-sectional dependence test
This test is used to test whether residuals are correlated across entities. This problem is especially likely to occur in data sets with long time-series, but few cross-sectional units. This is the case for some forecasting specifications used. While cross-sectional dependence could bias test results, it would not affect the coefficients obtained. The null hypothesis of the test is that the residuals are not correlated (i.e., one would hope to see a P-value of more than 0.05 on this test).

Serial correlation test
In the case of serial correlation, the residuals are correlated over time. This may cause the standard errors of coefficients to be too small, making coefficients appear statistically significant when in fact they are insignificant. The Wooldridge test for autocorrelation in panel data has the Null-hypothesis that there is no first-order autocorrelation, meaning that a P-value above 0.05 gives confidence in the accuracy of the standard errors.

Hausman test
The Hausman test tests for systematic differences between a consistent and an efficient estimator. No systematic differences in coefficients is the null hypothesis. The consistent model should be used when this is rejected. This can be used to decide between fixed (which is always consistent) and random (which is efficient under the null) effects estimation for panel data. Hausman test results are presented under all regression tables in the text. When the null hypothesis is not rejected, i.e., the P-value is higher than 0.05, this confirms that random-effects estimation is appropriate.

Another important assumption of the models is that there are no confounding variables that bias the results. This can also be tested using the Hausman test. To obtain a consistent estimate, the Model 4 with industry level panels is re-estimated using overall investment (as used in the owner-type estimations) as an instrument for industry-level investment. This is then compared to the basic model. The estimation results in Table A6 show that the null hypothesis that there are no systematic differences in coefficients cannot be rejected at the five per cent confidence level. This gives some reassurance that the estimates obtained throughout are unbiased.

Table A6: Hausman test

	RE model	IV model	Difference
Δ Number of filings (t-1)	0.47	0.17	0.29
Δ Real GDP	0.20	0.53	-0.33
EU dummy	10.82	-9.34	20.16
EU dummy * foreign	-9.09	-148.72	139.63
TM10 dummy	14.96	29.19	-14.23
TM10 dummy * first	95.25	68.33	26.92

Test: H0 = Difference in coefficients is not systematic	
X^2	12.4
$P>X^2$	0.054

Robustness checks

It is important that estimation results are robust to changes in the data and are not dependent on outliers. To test this, the models used for forecasting are re-estimated, leaving out one panel unit at a time. Table A7 shows the results for estimates based on owner-type panels (model 2). The estimated coefficients vary only slightly. The largest changes are observed when foreign owners are left out, which is not surprising given the panel's volatility after the introduction of the EU trade mark. However, all coefficients still remain equal in sign and similar in magnitude. Table A8 repeats this exercise for the models on industry level with similar results.

Table A7. Sensitivity of estimation to certain observations, owner-type panels					
	All panels	**W/o corporate**	**W/o individuals**	**W/o foreign**	**W/o first-time filers**
Δ Number of filings (t-1)	0.23***	0.17**	0.30***	0.23***	0.17*
	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
Δ Real GDP	1.80	1.00	1.83	1.36	1.94
	(1.31)	(1.09)	(1.40)	(1.25)	(1.52)
Δ Investment	3.13	1.03	3.43	2.96	1.10
	(3.28)	(2.73)	(3.49)	(3.15)	(3.78)
TM10 dummy	99.87	77.28	60.52	87.56	166.57
	(145.05)	(121.33)	(154.90)	(139.26)	(123.32)
TM10 dummy * first	245.77	129.92	152.99	266.48	0.00
	(199.41)	(166.63)	(211.75)	(192.36)	(.)
EU dummy	-38.86	-47.99	-55.84	3.49	-105.44
	(61.81)	(52.01)	(66.33)	(58.07)	(71.77)
EU dummy * foreign	-299.25**	-263.94***	-251.58**	0.00	-349.28**
	(94.68)	(75.39)	(94.90)	(.)	(112.05)
Constant	58.21	50.95	56.21	30.29	76.95
	(56.57)	(47.33)	(60.64)	(53.80)	(66.17)
Within R2	0.10	0.11	0.12	0.06	0.14
Between R2	0.43	0.34	0.50	0.90	0.40
Overall R2	0.14	0.11	0.16	0.11	0.15
RMSE	522.97	405.09	517.04	465.03	427.50
Number of observations	378	324	324	324	189
Number of groups	14	12	12	12	7

Table A8. Sensitivity of estimation to certain observations, industry level panels

	All panels	W/o corporate	W/o individuals	W/o foreign	W/o first-time filers
			Model 3		
TM10 dummy	68.88*	69.35**	44.93**	68.85*	61.85***
	(27.23)	(26.47)	(16.79)	(27.65)	(15.90)
TM10 dummy * first	63.81	95.94**	31.58	61.99	0.00
	(34.50)	(33.59)	(21.26)	(35.02)	(.)
Δ Regis'd businesses w/o employees (t-1)	-2.00***	-1.87***	-1.31***	-2.00***	-1.05**
	(0.47)	(0.46)	(0.29)	(0.48)	(0.36)
Δ Unreg'd businesses w/o employees (t-1)	0.23*	0.19*	0.18**	0.21*	0.14
	(0.09)	(0.09)	(0.06)	(0.10)	(0.07)
Δ Self-employment (t-1)	-290.55*	-239.61	-282.66**	-280.00*	-247.40*
	(139.45)	(135.41)	(86.03)	(141.57)	(105.19)
Constant	37.22*	36.22*	31.32**	40.38*	17.92
	(16.13)	(16.10)	(9.88)	(16.39)	(12.61)
Within R2	0.06	0.07	0.06	0.05	0.00
Between R2	0.08	0.08	0.12	0.07	0.00
Overall R2	0.05	0.07	0.05	0.05	0.05
RMSE	172.60	164.58	104.56	172.07	92.06
No. obs.	728	702	702	702	364
No. groups	56	54	54	54	28
			Model 4		
Δ Real GDP	0.48*	0.36	0.37	0.43*	0.43
	(0.23)	(0.21)	(0.20)	(0.17)	(0.25)
Δ Investment (t-1)	-0.39	-0.49	-0.31	-0.40	-0.28
	(0.56)	(0.53)	(0.50)	(0.42)	(0.62)
TM10 dummy	36.75	43.68	21.86	31.96	50.80*
	(29.68)	(28.06)	(26.67)	(22.28)	(24.31)
TM10 dummy * first	82.73*	111.95**	53.56	73.60*	0.00
	(40.62)	(38.49)	(36.21)	(30.67)	(.)
EU dummy	-12.36	-6.14	-17.50	-0.40	-32.56*
	(13.06)	(12.34)	(11.80)	(9.69)	(14.64)
EU dummy * foreign	-333.34***	-355.75***	-278.97***	0.00	-369.48***
	(40.91)	(40.11)	(31.11)	(.)	(39.31)

Table A8. Sensitivity of estimation to certain observations, industry level panels					
Constant	37.22*	36.22*	31.32**	40.38*	17.92
	(16.13)	(16.10)	(9.88)	(16.39)	(12.61)
Within R2	0.06	0.07	0.06	0.05	0.00
Between R2	0.08	0.08	0.12	0.07	0.00
Overall R2	0.05	0.07	0.05	0.05	0.05
RMSE	172.60	164.58	104.56	172.07	92.06
No. obs.	728	702	702	702	364
No. groups	56	54	54	54	28

Throughout, the models distinguish between first-time and repeat filers. However, the models only allow for differences in intercepts, but not in the other coefficients. Table A9 presents estimates for models where the independent variables are interacted with the "first" dummy. Therefore, separate parameters are estimated for first-time and repeat filers. However, all coefficients become insignificant. Even when testing for joint significance, the effects are statistically not different from zero. This suggests that allowing for differences in intercepts is enough, and that all variables have similar effects on first-time and repeat filers.

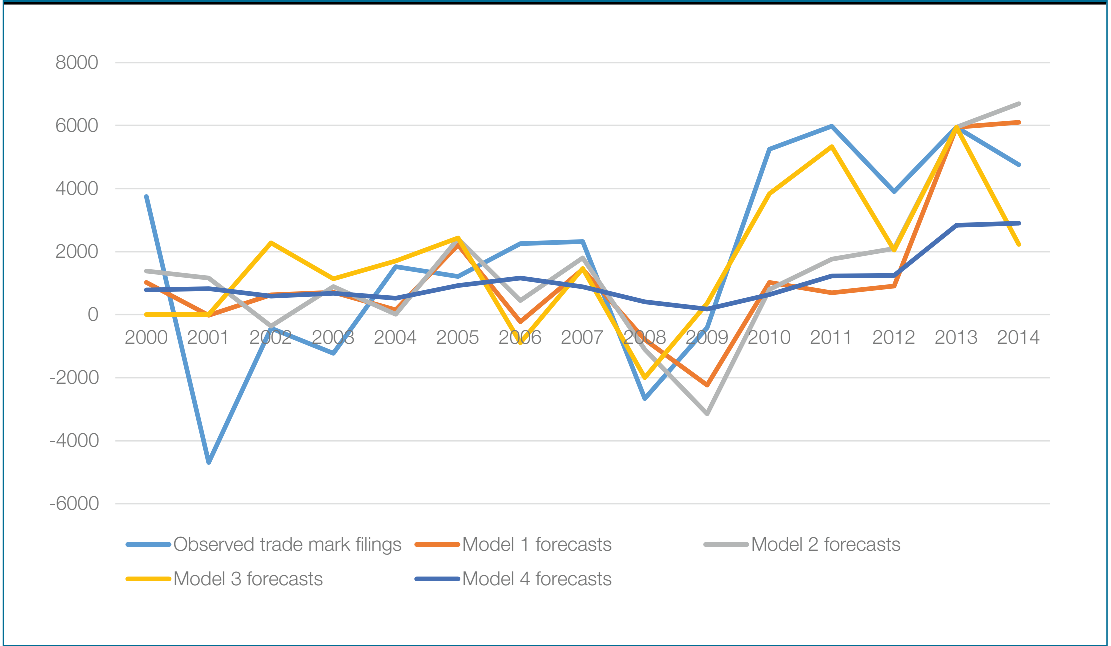
Table A9. Interaction effects for new filers

	Owner-type panels		Industry level panels	
Δ Real GDP	1.13	(1.78)		
Δ Real GDP * first	-0.29	(2.51)		
Δ Investment	2.14	(4.49)		
Δ Investment * first	5.14	(6.35)		
TM10 dummy	176.09	(145.35)	61.85*	(29.68)
TM10 dummy * first	265.44	(204.24)	77.87	(41.98)
Δ Regis'd businesses w/o employees (t-1)			-1.05	(0.66)
Δ Regis'd businesses w/o employees * first (t-1)			-1.91*	(0.94)
Δ Unreg'd businesses w/o employees (t-1)			0.14	(0.13)
Δ Unreg'd businesses w/o employees * first (t-1)			0.18	(0.19)
Δ Self-employment (t-1)			-247.40	(196.41)
Δ Self-employment * first (t-1)			-86.30	(277.77)
EU dummy	-15.76	(61.84)		
EU dummy * foreign	-585.49***	(130.90)		
First dummy	79.73	(123.33)	38.59	(32.17)
Constant	59.99	(94.46)	17.92	(22.75)
Within R2	0.11		0.07	
Between R2	0.15		0.08	
Overall R2	0.10		0.07	
RMSE	510.37		171.90	
Number of observations	378		728	
Number of groups	14		56	

Another way of looking at the forecasting ability of the models is by estimating the model only up to a certain point and forecasting from there on to compare with the observed values. For the predicted values in Figure A1, models were only estimated until 2011, and forecasts based on that data are produced for the years 2012 to 2014. The model specifications are the same as those used in the main text.

Until 2010, all models follow the observed values quite closely. While model 3 estimated for industry panels can capture the increase in filings from 2010 to 2011, it predicts too strong of a fall in filings thereafter. The steady increases predicted by the other models are too small to capture the actual rapid increase in filings.

Figure A1: In-sample forecasts of the change in trade mark filings



Appendix A3: Estimation with panel data

Panel data combine two types of data: they are longitudinal, but observe cross-sections at different points in time. When describing change over time, they can produce superior estimates than pooled data, as both the variation in the variable of interest as well as over different individuals or groups can be observed. However, the fact that the data are two-dimensional requires some adaptations to the classic OLS regression.

Consider fitting models of the form

$$y_{it} = \alpha + x_{it}\beta + \nu_i + \epsilon_{it} \tag{1}$$

In this model, $\nu_i + \epsilon_{it}$ is the error term that is of little interest, since estimates of β are required. ν_i is the unit-specific error term; it differs between units, but for any particular unit, its value is constant. ϵ_{it} is the "usual" error term with the usual properties: mean 0, uncorrelated with itself, uncorrelated with x, uncorrelated with ν, and homoscedastic.

Before making the assumptions necessary for estimation, some useful algebra can be performed on (1). Whatever the properties of ν_i and ϵ_{it}, if (1) is true, it must also be true that

$$\bar{y}_i = \alpha + \bar{x}_i\beta + \nu_i + \bar{\epsilon}_i \tag{2}$$

where a bar over a symbol represents that variable divided by the number of periods in the sample T. Subtracting (2) from (1), it must be equally true that

$$(y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i)\beta + (\epsilon_{it} - \bar{\epsilon}_i) \tag{3}$$

These three equations provide the basis for estimating β. Fixed-effects estimation – also known as the within estimator – amounts to using OLS to perform the estimation of (3). The between estimator amounts to using OLS to perform the estimation of (2). A third option, random-effects estimation, combines the between and within estimator as the (matrix) weighted average. In particular, the random-effects estimator turns out to be equivalent to the estimation of

$$(y_{it} - \theta\bar{y}_i) = (1-\theta)\alpha + (x_{it} - \theta\bar{x}_i)\beta + \{(1-\theta)\nu_i + (\epsilon_{it} - \theta\bar{\epsilon}_i)\} \tag{4}$$

where θ is a function of the variances of the two error terms.

Because the analysis here concerns change over time, the between estimator is of little interest here. There are some pros and cons to both the fixed- and the random-effects estimator. The fixed-effects estimator does away with all individual specific effects (the ν_i) by demeaning the variables first. This becomes a problem when variables that are fixed over time are to be included in the model. If there is reason to believe that differences across entities have some influence on the dependent variable, random-effects should be used.

However, the random-effects estimator requires that individual specific effects are random and uncorrelated with the independent variables. All individual characteristics that are correlated with other independent variables have to be controlled for. This can be difficult if some characteristics are unobservable. In estimating trade mark filings, the main reason to segment applicants into different groups is the assumption that there are systematic differences in the filing behaviour of e.g. companies and individuals. Therefore, the random-effects estimator was chosen to explicitly account for this fact.

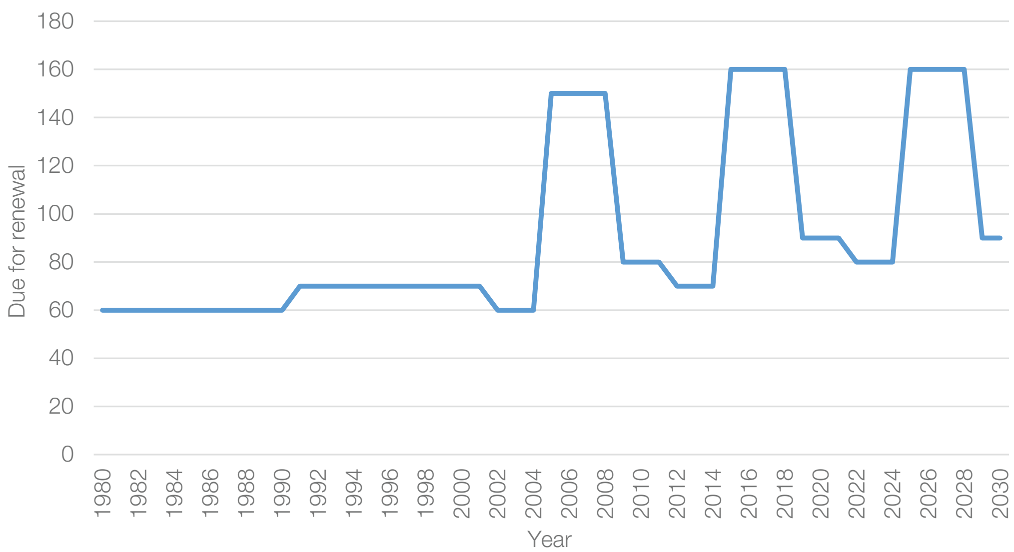
Appendix A4: Effect of the change in the renewal forecast horizon

Change in renewal horizon

Rules on renewal periods for trade marks have been changed recently, which results in a cyclical pattern of drops and increases in the number of trade marks that come due for renewal. Trade marks registered before 1995 were initially valid for seven years and had to be renewed every fourteen years thereafter. This changed in 1995, when the renewal horizon was uniformly changed to ten years for both new trade marks and older trade marks that came up for renewal after 1994.

As a result, there was a drop in trade marks due for renewal in 2002, fourteen years after the policy change. In 2010, there is a large increase of trade marks, triggered by those that already became due for renewal after 10 years. Figure A2 illustrates how this pattern continues in ten year-long cycles with smaller drops in renewals in each cycle.

Figure A2: Impact of changing renewal horizon



Effect on trade marks filed with priority

The change in the renewal horizon has some further knock-on effects on trade marks filed or up for renewal around the date of the change. In some cases, this causes discrepancies between the renewal date listed on the register and the renewal date computed from the filing date. A major cause of discrepancies are trade marks filed with “priority”. If an applicant has applied for a trade mark outside the UK in a period of no more than six months before filing the UK application, then they can claim priority from the earlier trade mark. This also means that the filing date for purposes of calculating the renewal date will be the date of original filing outside the UK. However, the database records the filing date as the date of filing in the UK. Therefore, a trade mark filed in early 2015 under priority may still fall under the old renewal scheme of 7 + 14 years if it was first filed outside the UK in 1994. This affects not only newly filed trade marks around the policy change, but also those that came up for renewal.

The due to renew date on the register is the correct renewal date. However, using this as the basis to compute earlier renewals is not feasible since the change in the renewal horizon means that – for trade marks due to be renewed between 2005-2008 – it is not possible to tell whether they were filed in 1995-1998 or 1991-1994. Therefore, there would be discrepancies between renewals dates modelled from the official filing dates and the due to renew date on the register. These differences only occur in a small number of years, and even for those years are too small to affect results materially. Table A10 contrasts the number of trade marks due to be renewed according to the database and from computations based on the filing date on the database.

Table A10: Trade marks actually due to be renewed vs. inferred

	Actual	Inferred	Difference
	Did renew		
2005	29,357	33085	-3,728
2006	30,314	30312	2
2007	33,639	33747	-108
2008	27,723	29593	-1,870
2009	19,549	19778	-229
2010	20,486	20759	-273
2011	18,142	22952	-4,810
2012	12,815	12740	75
2013	11,884	11898	-14
2014	15,634	12406	3,228
	Due to be renewed		
2015	51,377	55978	-4,601
2016	56,094	55720	374
2017	61,717	61445	272
2018	53,057	54033	-976
2019	44,102	44315	-213
2020	47,616	47861	-245

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