EUIPO
EUROPEAN UNION
INTELLECTUAL PROPERTY OFFICE

Modelling and forecasting European trade mark and design filings

July 2023

MODELLING AND FORECASTING EUROPEAN TRADE MARK AND DESIGN FILINGS

Catalogue number: TB-09-23-268-EN-N ISBN: 978-92-9156-341-8 DOI : 10.2814/463929

Acknowledgements

This paper was prepared by Carolina Arias Burgos, Economist in the Observatory Department at the EUIPO with the assistance of Nathan Wajsman, Chief Economist of the EUIPO.

The author is grateful for comments on a previous version of this paper from Spyridon Spyratos from the Digital Transformation Department and Paola Paulucci from the Corporate Governance Service of the European Union Intellectual Property Office (EUIPO); Ingo Kuhnert and Christoph Maier from the European Commission's Directorate General for Economic and Financial Affairs (DG ECFIN) B3 Unit (Models and Databases); and Julian Kolev and Gerard Torres from the Office of the Chief Economist (OCE) of the United States Patent and Trademark Office (USPTO).

Table of Contents

Acronyms and Abbreviations

AMECO	Annual Macroeconomic Database
ARIMA	Autoregressive integrated moving average
BCS	Business and Consumer Surveys
CFC	Consumption of Fixed Capital
COVID	Coronavirus Disease
DG-ECFIN	Directorate General for Economic and Financial Affairs
EC	European Commission
ECB	European Central Bank
ESA	European System of Accounts
EU	European Union
EUIPO	European Union Intellectual Property Office
Eurostat	Statistical Office of the European Union
EUTM	European Union Trade Mark
FCE	Final Consumption Expenditure
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
IMF	International Monetary Fund
IP	Intellectual Property
IPR	Intellectual Property Right
NA	National Accounts
NFCF	Net Fixed Capital Formation
OECD	Organisation for Economic Co-operation and Development
RCD	Registered Community Design
RoW	Rest of the World
RRF	Recovery and Resilience Facility
UK	United Kingdom
UKIPO	United Kingdom Intellectual Property Office
US	United States
USPTO	United States Patent and Trademark Office
VAR	Vector Autoregressive
WIPO	World Intellectual Property Organization

Executive Summary

Filings of intellectual property rights (IPRs) have suffered even more volatility since 2020 than other economic indicators, making it more difficult for intellectual property (IP) offices to accurately predict volumes of filings for budget and staff planning purposes.

In an effort to improve forecasting of trade mark and design filings, the European Union Intellectual Property Office (EUIPO) has analysed the relationship between trends in trade mark and design filings and other economic indicators. The analysis showed that a multivariate model with the best statistical properties and forecasting performance includes confidence indicators from industry and service sectors, consumers' confidence indicator, private consumption, investment, and European Union (EU) grants.

This paper introduces the concept of Granger causality to understand which variables are useful in forecasting European Union Trade Mark (EUTM) and Registered Community Design (RCD) filings.

- The EUTM filings forecasts are improved by including data on RCD filings, a confidence indicator from the industry sector and net capital transactions with the rest of the world (RoW) which includes the Recovery and Resilience Facility (RRF) grants paid by EU institutions.

- The RCD filings forecasts are improved by including confidence indicators for consumers and the service sector and private consumption.

- Finally, although it is out of scope of this paper, EUTM filings could be a leading indicator at EU level for private consumption and consumer confidence.

The model proposed in this paper allows for generation of filings forecasts conditional on the European Commission's forecasts of consumption, investment and net capital transactions with RoW including EU RRF grants.

1 Introduction

The uncertainty around the economic development of the EU during the COVID-19 crisis has become even more pronounced with the Russian invasion of Ukraine and subsequent sanctions and other measures. The impact of inflation, rising interest rates and low confidence in the economy should not be underestimated and it has led to an increasing interest in short-term data and forecast methods.

Intellectual Property Rights (IPRs) are rights associated with intangible assets granted to persons or firms. They usually give the owner, creator or inventor an exclusive right over the use of their creation or invention for a certain period of time. Some examples of IPRs are trade marks, designs, patents or copyright.

IPRs are also a measure of innovation, reflecting decisions of economic actors to invest and bring new products and services to the marketplace. They have also suffered the volatility of other economic indicators, making it more difficult for intellectual property (IP) offices to accurately predict volumes of filings and hence their fee income in recent years. There is a need to understand the relationship between the evolution of IPRs and other economic indicators. This paper presents an analysis of European trade marks and designs from an economic point of view and a forecasting model that makes use of the European Commission's forecasts of economic indicators.

European Union Trade Marks (EUTMs) are registered at the European Union Intellectual Property Office (EUIPO) and are valid in all European Union (EU) Member States. The increased demand for EUTMs in the last decade, with a record of almost 200 000 applications in 2021, reaching a cumulative total of 2.5 million EUTM applications (since the start of EUIPO operations in 1996) in March 2022, was followed by a sudden slowdown and sharp decrease of filings.

Registered Community Design (RCD) filings reached a cumulative total of 1.8 million designs (since the start of the RCD in 2003), with an average annual growth rate of 4.5 % between 2010 and 2020, stabilised in 2021 and experienced an unexpected decrease of 7 % in 2022.

The European trade mark and design filings have been available in the EUIPO databases since 1996 for EUTMs and since 2003 for RCDs. Time series analysis consists of the analysis of a sequence of data points collected over a period of time to understand past trends, what factors influence those trends, and to foresee future developments. The EUIPO, as any other economic actor, requires forecasts of volumes of filings to take decisions on future budget and the planning of its activities, including staff planning. Forecasting, even with the most sophisticated methods and data, is full of risks in volatile periods but is essential for efficient planning.

This paper presents detailed results of the analysis of European trade mark and design filings with the purpose of giving more transparency to the process of decision making. Section 2 presents a univariate time series analysis of trade mark and design filings to understand the trends in recent years, exclusively for forecasting purposes. Section 3 presents a multivariate model, adding economic indicators of the EU economy to improve forecasting of EUIPO filings, and section 4 uses the best multivariate model to produce forecasts of EUTM and RCD filings, conditional on externally forecasted values of economic indicators. Finally, section 5 presents some conclusions and ideas for future research.

2 Univariate analysis of trade mark and design filings

The continuous increase of European trade mark filings in the last two decades, with an average annual growth rate of 7 %, was followed by two-digit annual growth rates in 2020 and 2021 and a 12 % decrease in 2022 in the number of EUTM filings. RCD filings registered an average annual growth rate since 2003 of 5 % and a decrease of 7 % in 2022. These changing trends can be partially explained by an extraordinary increase of filings from China in 2020 and 2021, surpassing Germany as the leading country in the number of both EUTM and RCD applications([1]). The end of the Chinese government subsidies ([2]) encouraging IPR filings in China and abroad could be one of the reasons behind the decrease of EUTM and RCD applications from Chinese firms, which explains more than half of the overall decrease in total filings in 2022.

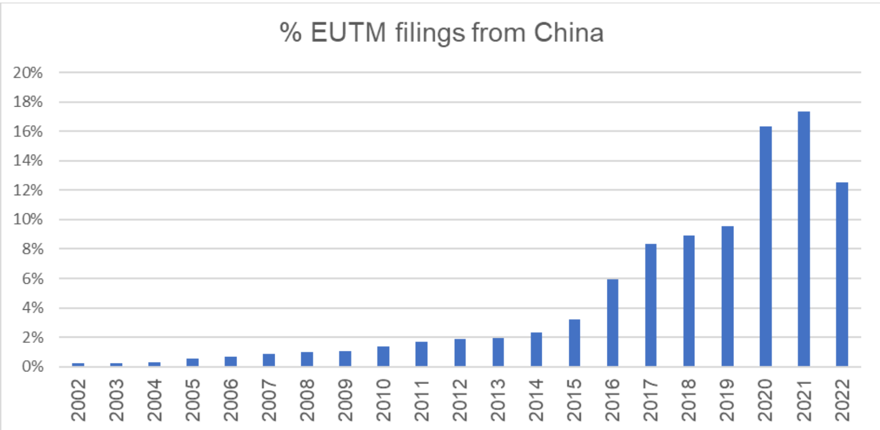
([1]) As shown in USPTO (2021), China's filings under the Madrid Protocol and Patent Cooperation Treaty, surpassed those of the United States for the first time in 2019. The increase of ecommerce during COVID-19 pandemic could partially explain the surge of IPR applications from China in different territories.
([2]) See USPTO (2021) and Stemler, T. (2021) for more details on the Chinese IP subsidies.

Until 2020, forecasting filings based on univariate AutoRegressive Integrated Moving Average (ARIMA) models provided accurate predictions, although in 2016 the result of the referendum on the withdrawal of the United Kingdom from the European Union required an intervention model in the EUTM time series to take into account the impact of the future change of the territory of protection of European IPRs. The intervention model of a Level Shift in 2016 in the univariate model absorbed the anticipated decrease in filings in response to the withdrawal of the United Kingdom from the EU.

Furthermore, the extraordinary increase in Chinese filings impacted significantly on the total number of filings, and the subsequent decrease of filings in 2022 resulted in the total number of filings returning to normal levels.

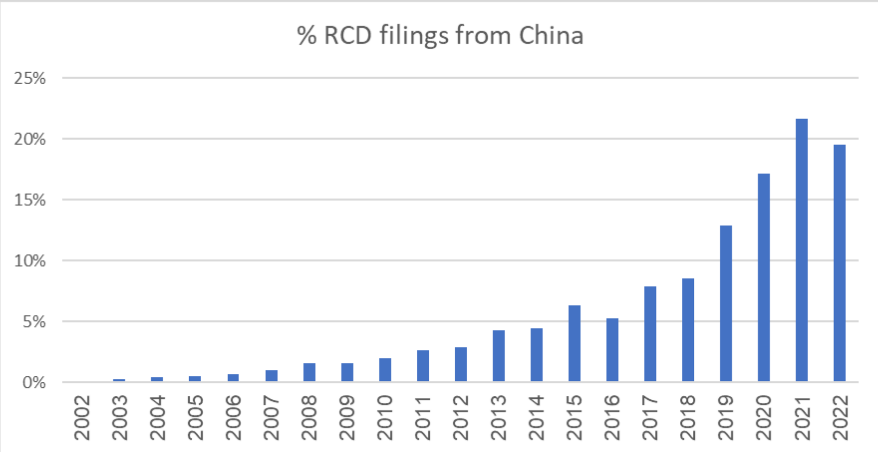
Figures 1 and 2 reflect the increase of the share of Chinese EUTM and RCD filings in 2020 and 2021 and the decline in 2022 when EUTM filings from China were below their level of 2 years earlier, while Chinese RCD filings in 2022 were at the same level as in 2020.

Figure 1: Share of EUTM filings from China, 2002-2022.



Source: Author's own calculations based on the EUTM database.

Figure 2: Share of RCD filings from China, 2002-2022.



Source: Author's own calculations based on the RCD database.

The apparent lack of economic reasons behind this changing pattern of Chinese filings and their great impact on total filings, added to the general volatility context, made it difficult (or even impossible) to forecast the expected volumes of EUIPO filings in the last 2 years.

The purpose of this section is not to analyse the impact of Chinese filings but to model this unusual trend to avoid inaccurate forecasts of EUTM and RCD filings.

2.1 EUTM filings analysis

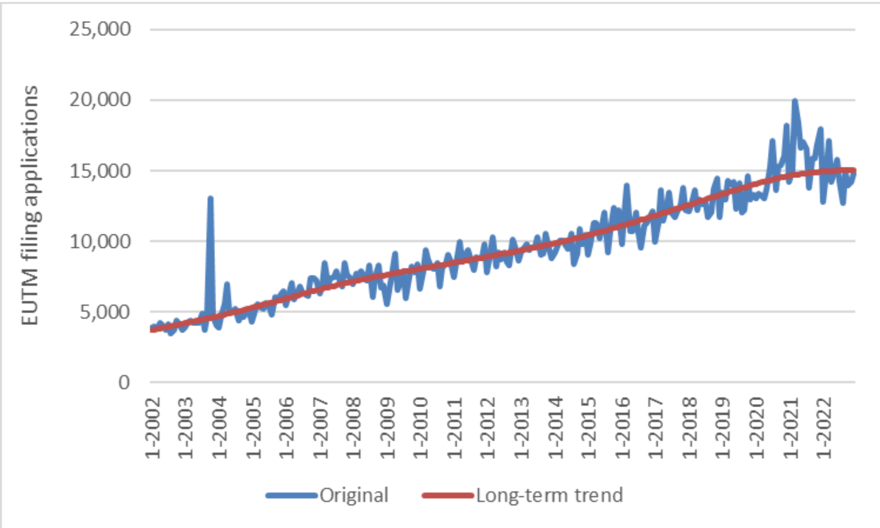
The evolution of EUTM filings is analysed for the period 2002-2022, with monthly time series extracted from the EUIPO registers.

Univariate ARIMA models considering all EUTM filings are estimated and decomposed into their components: long-term trend, cycle, seasonal component, and irregular component as well as all transitory components including outliers and calendar effects [3].

[3] Univariate time series analysis was carried out based on the automatic procedure of TRAMO/SEATS program from Banco de España.

Figure 3 shows the monthly time series of EUTM filings and its long-term trend. It shows how filings in 2020 and 2021 moved away from the trend and returned to it in 2022. The decomposition of the time series detected an exceptional cycle between June 2020 and December 2021 of about 10 % additional filings.

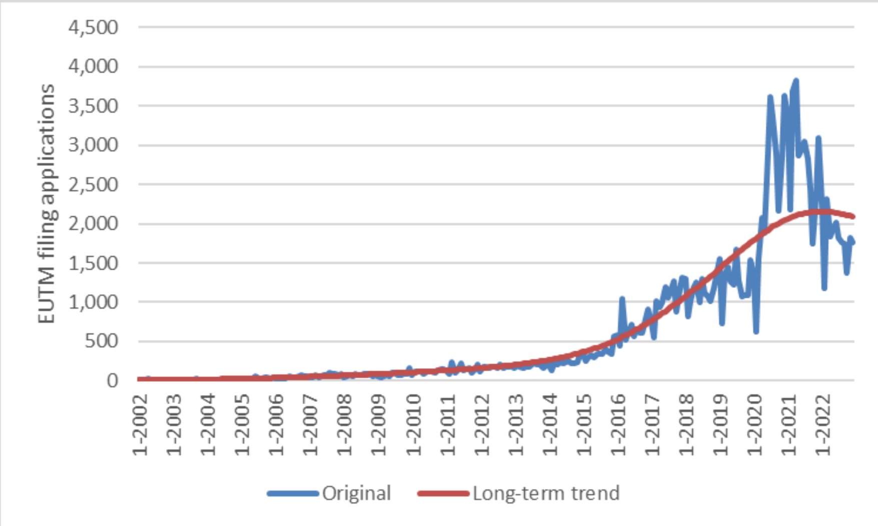
Figure 3: EUTM monthly filings and long-term trend, 2002-2022.



Source: Author's own calculations based on the EUTM database.

When filings from Chinese firms are analysed separately, the deviation from the long-term trend is more pronounced, reaching 50 % extra filings in the first half of 2021. In both cases, the period of extraordinary number of filings ended at the beginning of 2022.

Figure 4: EUTM monthly filings from China and long-term trend, 2002-2022.



Source: Author's own calculations based on the EUTM database.

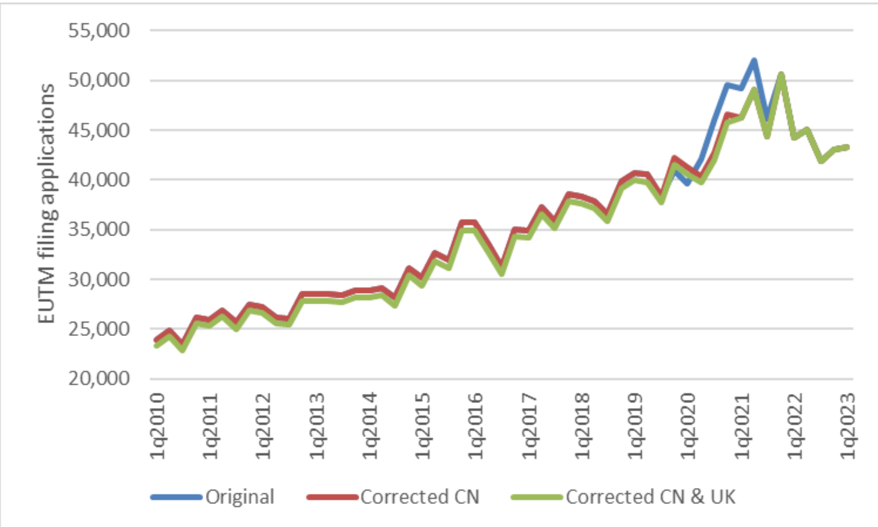
Other events affecting EUTM filings were the referendum on the withdrawal of the United Kingdom from the EU in June 2016 and the end of the transition period of the withdrawal agreement in December 2021, reflected as two declines of filings from this country of much lower magnitude (compared with the impact of Chinese filings): a monthly average decline of 200 filings beginning in 2016 when firms started to anticipate the impact of the withdrawal.

In view of the impact of those extraordinary events, in past forecasting exercises, the Chinese trade mark filings were analysed separately from the rest of the filings, and the impact of the UK's withdrawal from the EU was modelled with an intervention model. Both events came to an end in 2022 and filings from China and the United Kingdom returned to their normal (or new normal) trends as from 2022. This justifies the use of time series, filtered for the exceptional Chinese filings in 2020 and 2021 and the impact of Brexit, in the following sections.

Another result that emerged from the univariate analysis of filings is the presence of calendar effects only in EUTM filings registered directly at the EUIPO, while time series of international filings, registered at the World Intellectual Property Organization (WIPO), do not reveal calendar effects but an irregular seasonality. This is probably explained by the assignation of filings to the month in which they are received in batches in Alicante and not the month when they are filed in Geneva. When univariate ARIMA models based on monthly and quarterly time series are compared, quarterly models turned out to be clearly superior based on diagnostic tests [4], out-of-sample forecasting errors, number of outliers, simplicity of the models and stability of calendar effects.

In the following steps, the EUTM filings time series used for forecasting models are quarterly series corrected for Chinese filings exceeding the long-term trend during 2020 and 2021, and the United Kingdom (UK) filings corrected until 2022 to eliminate the Level Shift caused by Brexit. Original and corrected quarterly filings and their annual rates of growth are shown in figures 5 and 6, starting in 2010 until the first quarter of 2023. The correction results in an average of 1 000 filings less per quarter and a maximum of 4 000 filings less in the third quarter of 2020. From 2022 onwards, the time series corresponds to the actual filings.

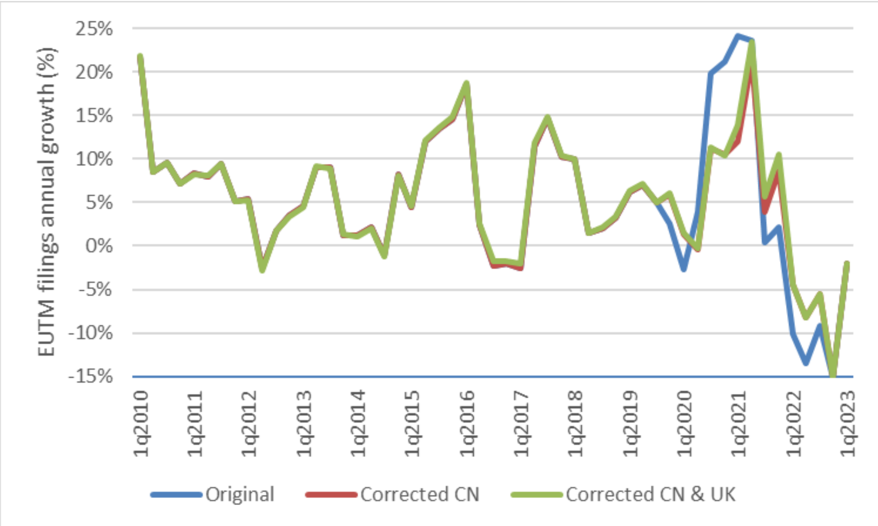
Figure 5: EUTM quarterly filings: original and time series corrected for Chinese and UK filings, 1q2010-1q2023.



Source: Author's own calculations based on the EUTM database.

(4) Analysis of residuals tests: autocorrelation, normality, randomness, mean and variance stability, seasonality and calendar effects tests.

Figure 6: EUTM quarterly filings annual rates of growth (%): original and time series corrected for Chinese and UK filings, 1q2010-1q2023.

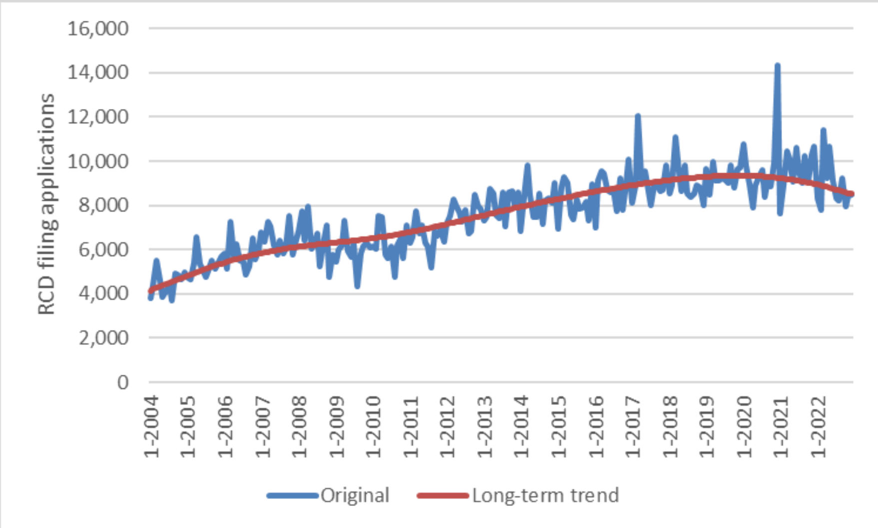


Source: Author's own calculations based on the EUTM database.

2.2 RCD filings analysis

RCD filings monthly time series was also analysed, and Chinese and UK filings showed similar irregular movements, although with a lower impact on total filings compared with EUTM filings. Chinese filings exceeding the long-term trend are more than 20 % of filings in 2020 and 2021 and the impact of the UKs withdrawal from the EU is an average of 250 RCD filings per month since 2021, later than its impact on EUTM filings.

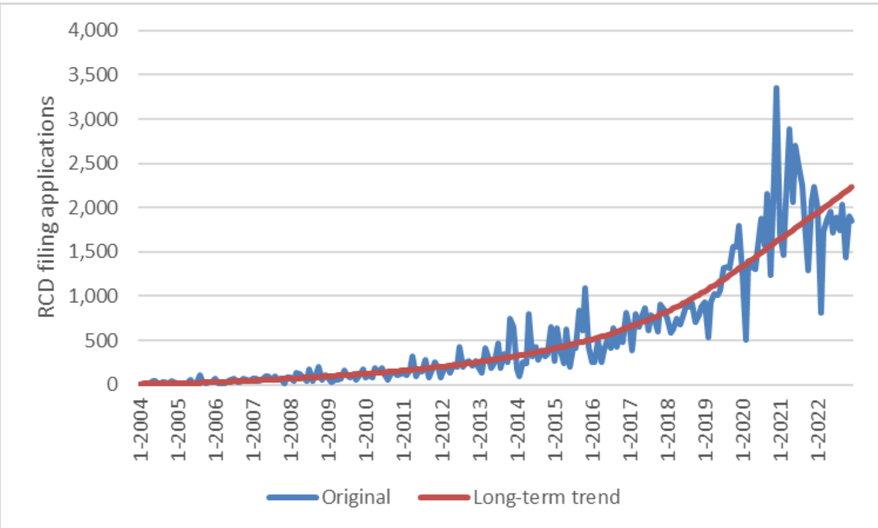
Figure 7: RCD monthly filings and long-term trend, 2004-2022



Source: Author's own calculations based on the RCD database.

As shown in figure 8, the period of exceptional Chinese RCD filings is more concentrated in the first half of 2021.

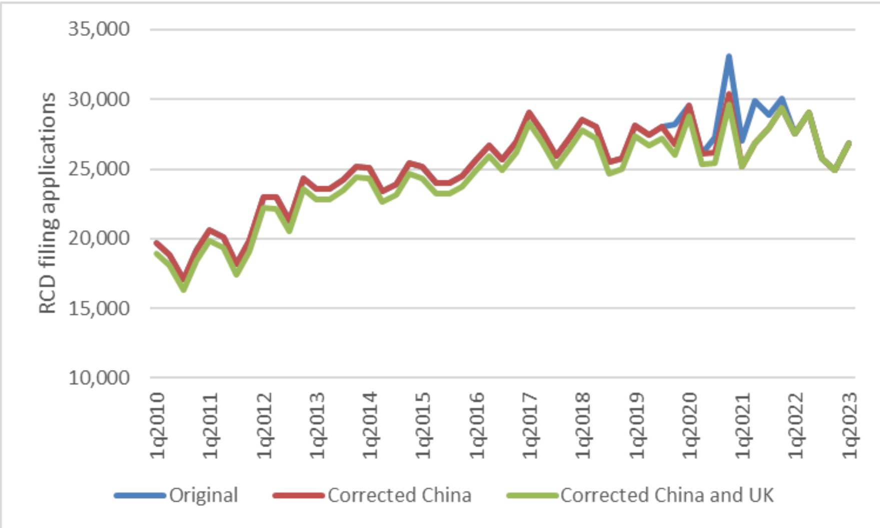
Figure 8: RCD monthly filings from China and long-term trend, 2004-2022.



Source: Author's own calculations based on the RCD database.

Although the advantages of quarterly univariate models compared with monthly models are not evident for RCD filings, the multivariate model proposed in section 3 is based on quarterly time series for both types of IPR filings and filtered for the excess of Chinese filings over the long-term trend in 2020 and 2021 and the effect of Brexit on RCD filings. From 2022 onwards, both time series are not corrected and so represent the actual number of filings received at the EUIPO and international filings received from WIPO. Total quarterly filings of original time series and corrected for RCD filings from China and the United Kingdom are shown in figure 9 and their annual rates of growth in figure 10.

Figure 9: RCD quarterly filings: original and time series corrected for Chinese and UK filings, 1q2010-1q2023.



Source: Author's own calculations based on the RCD database.

Figure 10: RCD quarterly filings annual rates of growth (%): original and time series corrected for Chinese and UK filings, 1q2010-1q2023.

Source: Author's own calculations based on the RCD database.

3 Multivariate models

Until 2021, the forecasting of filing volumes at the EUIPO was based on historical trends and univariate ARIMA models with the two monthly time series of EUTM and RCD filings analysed separately, and no external influence added besides intervention models for the UKs withdrawal from the EU and COVID-19 impacts([5]). Univariate ARIMA models are appropriate when the current trend of a time series can be explained by its past behaviour and the future fluctuations are expected to continue with a similar pattern.

However, the value of one variable is often not only related to its own past values and changes in other variables can be more informative. European IPR filings can be considered an economic

([5]) The impact of Brexit was modelled as a Level Shift intervention starting in 2016 and COVID-19 impact was a Temporary Change since 2020. Both interventions were added to the ARIMA model automatically identified by the TRAMO/SEATS software from Banco de España.

indicator of confidence in the EU internal market (6), anticipating future developments of the EU economy. At the same time, it is likely that firms' decisions to enter new markets and file IPRs depend on the evolution of the economy and in that case, IPR applications could follow the evolution of the EU economy. It is then not always clear whether IP filings are the cause or the consequence of economic developments. IPR filings and EU economic indicators could be tested for a bidirectional relationship with several variables affecting each other. In that case, it makes sense to use multiple time series in forecasting models without predetermination of which variables are predictors.

VAR (Vector AutoRegressive) models are a natural extension of the univariate AutoRegressive (AR) models to dynamic multivariate time series. It is one of the most popular multivariate methods. It is flexible and easy to use and understand. They have proved to be especially useful for describing the dynamic behaviour of economic time series and for forecasting, providing superior forecasts to those from univariate models and allowing forecasts to be made conditional on the potential future trends of specific variables in the model. In this framework, all variables are treated symmetrically. They are all modelled as if they all influence each other equally, or in more formal terminology, all variables are treated as 'endogenous'.

A criticism sometimes levelled against VARs is the absence of economic theory behind the models. Nevertheless, the selection of variables to be included in the model should be justified based on economic rationality and previous knowledge of variables that influence each other in the system. Although a direct interpretation of the coefficients in VAR models is difficult, their usefulness for forecasting purposes has been demonstrated.

Some examples of the use of VAR models for forecasting purposes are: the European Central Bank (ECB) (7); the International Monetary Fund (IMF) (8); the European Commission's Directorate General for Economic and Financial Affairs (EC DG-ECFIN) (9); and the Organisation for Economic Co-operation and Development (OECD) (10).

---

(6) The USPTO (2019) argues that aggregated trade mark data reflecting firm-level decisions are leading economic indicators that can help predict business cycles. An internal EUIPO document has also found that EUTM filings are leading indicators for domestic demand in the EU.
(7) https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2461~fe732949ee.en.pdf.
(8) https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Forecasting-the-Nominal-Brent-Oil-Price-with-VARs-One-Model-Fits-All-43423.
(9) https://ec.europa.eu/eurostat/documents/3888793/5828269/KS-AN-03-070-EN.PDF.pdf/36cf9219-0ecb-41b3-913a-1c8ae2dceafe?t=1414779008000.
(10) https://www.oecd.org/economy/growth/38806703.pdf.

Additionally, Granger causality tests can be run for estimated VAR models, helping to understand which variables are useful in forecasting other variables in the sense that the knowledge of their future developments improves the forecasting compared with the univariate model, as will be explained in sub-section 3.4. Granger causality only provides information about forecasting ability, it does not provide insight into the true causal relationship between two variables and is hence used in this paper solely to improve forecasting models.

A VAR(p) model explains each variable by the past values of all variables in the model, with p lagged observations, as expressed in the example of a 4-variable VAR(2) model in equation 1.

Equation 1: matrix representation of VAR(2).

$$\begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{pmatrix}_t = \begin{pmatrix} \alpha_{111} & \cdots & \alpha_{114} \\ \vdots & \ddots & \vdots \\ \alpha_{141} & \cdots & \alpha_{144} \end{pmatrix} * \begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{pmatrix}_{t-1} + \begin{pmatrix} \alpha_{211} & \cdots & \alpha_{214} \\ \vdots & \ddots & \vdots \\ \alpha_{241} & \cdots & \alpha_{244} \end{pmatrix} * \begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{pmatrix}_{t-2} + \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{pmatrix}_t$$

where each of the four variables (Y_1, Y_2, Y_3, Y_4) is explained by past values of all the variables with up to two lags (Y_{it-1}, Y_{it-2}) where i=1,2,3,4.

Equation 2: ith-equation of VAR(2).

$$Y_{it} = f\left(Y_{1t-1}, Y_{1t-2}, Y_{2t-1}, Y_{2t-2}, Y_{3t-1}, Y_{3t-2}, Y_{4t-1}, Y_{4t-2}\right) + u_{it}$$

The selection of the relevant variables and the appropriate number of lags (also referred to as the VAR order) are based on statistical tests (11). Then, the values of the parameters are estimated, and the best model is used to forecast the variables of interest (EUTM and RCD filings). VAR is a reduced form model, which captures the dynamic properties of the variables, and it is appropriate for forecasting purposes but not for structural analyses.

The forecasting model proposed should be as simple as possible, based as far as possible on economic considerations and making the most of all available data as endogenous variables. There

(11) The following tests are taken into consideration for the determination of the VAR order or number of lags (p): Akaike (AIC), Schwarz-Bayes (SBIC), Hannan-Quin (HQIC), Information Criteria and Final Prediction Error (FPE). Care should be taken when using the AIC as it tends to choose large numbers of lags.

are two decisions to make when using a VAR to forecast, namely how many variables (denoted by k) and how many lags (denoted by p) should be included in the system. The number of coefficients to be estimated in a VAR is equal to $k+pk^2$ (or 1+pk per equation) so that increasing the number of variables and lags results in many parameters to estimate relative to the number of observations, missing degrees of freedom, low precision of estimated parameters, and high forecasting errors. In practice, it is usual to keep k small and include only variables that are correlated with each other, and useful in forecasting.

Although a VAR model treats all variables equally, the purpose of this paper is to find a multivariate model that improves forecasting of EUTM and RCD filings. Sub-section 3.1 details the variables that are considered a priori to be informative for the forecasting of EUTM and RCD filings. Sub-section 3.2 informs how to deal with different periodicity of time series and sub-section 3.3 presents the results of information criteria and other diagnostic tests used to select the appropriate VAR model for forecasting of filings. The Granger causality relationships of the selected VAR model and Impulse Response analysis are presented in sub-section 3.4, to understand which variables have the highest impact in the forecasting of the filings time series.

3.1 Selection of variables

The purpose of the VAR model is to improve the forecasting of EUTM and RCD filings by adding to the information contained in the past values of both time series additional information about the evolution of other economic indicators. When future developments of some of the variables in the model are known (or can be foreseen), the VAR model can be used to generate forecasts conditional on those variables. To generate conditional forecasts, the main sources of data are the European Commission's Directorate General for Economic and Financial Affairs (DG-ECFIN) short-term macroeconomic forecasts for the EU (12) published in the Annual Macro-ECOnomic database (AMECO) (13) which is updated twice a year with Eurostat's statistics, and the European Commission's Spring and Autumn forecasts. The future values of the macroeconomic indicators can then be included in the VAR model and used to generate conditional forecasts for EUTM and RCD filings for the current and the following year.

(12) https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/economic-forecasts_en.
(13) https://economy-finance.ec.europa.eu/economic-research-and-databases/economic-databases/ameco-database_en.

The selection of the set of variables to include in the VAR model is based on previous cyclical analysis([14]) of filings and the main economic indicators, and on economic rationality.

EUTMs and RCDs are registered to protect trade marks and designs in all EU Member States. At an individual level, these IPRs help distinguish a firm's products or services from those of other firms; on the aggregated level they reflect the economic confidence in the EU internal market. The filing activity in the EUIPO is expected to be driven by EU domestic demand([15]) components (consumption and investment), and changes in confidence in the EU economy([16]).

Based on this economic rationality, EUTM and RCD filings' trends were compared with selected National Accounts (NA) indicators for domestic demand, consumption, and investment, from AMECO, as well as confidence indicators produced by DG-ECFIN and downloaded from Eurostat([17]).

NA economic indicators are defined in the European System of Accounts (ESA 2010)([18]). The NA indicators available in AMECO that could be a priori useful for forecasting EUTM and RCD filings are: Gross Domestic Product (GDP); Domestic Demand; Gross and Net Fixed Capital Formation (GFCF and NFCF)([19]), private Final Consumption Expenditure (FCE)([20]) and net capital transactions with the rest of the world (RoW)([21]). Domestic Demand presented a closer cyclical correspondence with IPR filings than GDP, as explained in footnote 15: EUTMs and RCDs are valid in the EU territory and then should be correlated with economic developments in the internal market and not with

---

([14]) The cyclical analysis was carried out by smoothing time series to eliminate erratic movements with program <F> from the Spanish Statistical Institute (INE). This program uses specific filters like Hoddrick-Prescott, Butterworth band-pass. More details in Abad and Quilis (2004).

([15]) Domestic demand is the sum of household and government consumption and private and public investment, and it is equivalent to Gross Domestic Product (GDP) minus exports and plus imports. Extra-EU exports are sales in non-EU Member States and they are not expected to be corelated with IP filings valid in the EU territory. Imports into the EU (from outside the EU) could result in increased IP filings valid in the internal market. Additional to the economic rationality, the cyclical behaviour of GDP and domestic demand was compared with EUTM and RCD filings showing a closer relationship of both filings time series with domestic demand.

([16]) It could also be possible that filings of European IPRs from non-EU firms are driven by the economic situation and confidence in their home countries.

([17]) https://ec.europa.eu/eurostat/web/products-datasets/-/teibs020.

([18]) https://ec.europa.eu/eurostat/documents/3859598/5925693/KS-02-13-269-EN.PDF/44cd9d01-bc64-40e5-bd40-d17df0c69334.

([19]) GFCF is the sum of NFCF and Consumption of Fixed Capital (CFC) that represents the decline in value of fixed assets as a result of the normal use and obsolescence or depreciation.

([20]) Private FCE not including public government consumption.

([21]) Net capital transactions with the RoW is the balance between capital transfers received and paid from/to the RoW, including investment grants paid by the institutions of the EU such as those from the Recovery and Resilience Facility (RRF).

exports from the EU Member States to third countries. Domestic Demand components are investment (or GFCF/NFCF in NA jargon) and final consumption (including both public and private final consumption expenditure). As explained in EPO/EUIPO (2022), the activity of the government is not intensive in the use of IPRs so that it is expected that private consumption explains the evolution of IPR filings in the EU better than public consumption. Finally, the capital transfers with the RoW include, among other capital transfers, Recovery and Resilience Facility (RRF) grants paid by EU institutions, which are projected to reach extraordinary levels between 2021 and 2024 and are a driver for public and private investment(22). Based on that, the NA variables selected to test different VAR models in sub-section 3.4 are: Domestic Demand (including and excluding inventories), GFCF, NFCF, private FCE and net capital transactions with the RoW. All NA variables are used at constant prices except the net capital transactions with the RoW, which is only available in AMECO at current prices. It has been deflated using the GDP deflator.

Confidence indicators analysed are based on Business and Consumer Surveys (BCS)(23), a Commission Joint Harmonised EU programme. These surveys supply a wide range of information on current economic activity and its perspectives based on the opinions of economic actors, such as business and consumers. The information provided is essential for economic surveillance, short-term forecasting, and economic research. The European Commission (DG-ECFIN) estimates the Economic Sentiment Indicator (ESI) as a composite indicator based on six individual confidence indicators and provided also by sector (industry, construction, retail trade and services) as well as an indicator for consumer confidence. For the purpose of this analysis, the monthly sectorial indices are standardised to correct for differences in means and standard deviations applying the same method used for the ESI, and subsequently aggregated by quarter.

Equation 3: Standardisation method(24) applied to confidence indicators.
For each individual index, j=1,2, ..., 6

(1) $$Y_{jt} = \frac{X_{jt} - \bar{X}}{S_j} \quad \text{where } \bar{X}_j = \frac{1}{T'} \sum_{t=1}^{T'} X_{jt} \quad \text{and } S_j = \sqrt{\frac{1}{T'-1} \sum_{t=1}^{T'} (X_{jt} - \bar{X}_j)^2}$$

(22) EC DG-ECFIN (2023). 'Half of the increase in public investment between 2019 and 2024 is related to investment financed by the EU, particularly by the RRF'.
(23) https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys_en.
(24) https://ec.europa.eu/info/files/user-guide-joint-harmonised-eu-programme-business-and-consumer-surveys_en.

(2) $Z_{jt} = Y_{jt} * 10 + 100$

The moments (means and standard deviations) in (1) are computed over a frozen sample to avoid monthly revisions, starting from January 2000(25). The end-point of the sample, which is updated once a year in January, corresponds, in any given year t, to December of the year t-1. In (2), the resulting standardised indexes are scaled to have a long-term mean of 100 and a standard deviation of 10.

These confidence indicators were compared with EUTM and RCD filings, and those with the highest cyclical correspondence were the industry and service sectors as well as the consumer confidence indicator. Based on a previous analysis from the EPO and the EUIPO(26), most of the industries that make intensive use of European trade marks and designs are in the industry and service sectors, with low or no representation in construction, public services and agriculture. Additionally, the consumer confidence indicator is a leading indicator for private consumption, which is an important component of the domestic demand.

3.2 Periodicity and transformation of time series

NA indicators are available annually and quarterly and confidence indicators are monthly indicators. At first, it seemed preferable to follow the evolution of filings at the higher frequency and traditionally the EUIPO has analysed monthly filings. However, a significant share of filings (about 20 % of EUTM and about 15 % of RCD filings in 2021) are international registrations from WIPO and they are assigned to the month when they are received at the EUIPO, and not the month when they are registered in WIPO. This explains irregular seasonal and calendar effects detected in the univariate analysis of EUTM filings. Additionally, as mentioned above, the ARIMA models that were estimated showed superior econometric results and produced much better forecasts when quarterly time series were used.

(25) As explained in the BCS user guide, the starting point is 2000 to allow meaningful comparisons of the indicators across time and to ensure a higher degree of cross-country comparability.
(26) EPO/EUIPO (2022).

As explained in section 2, there are two events that resulted in extraordinary increases or decreases of filings not reflecting economic phenomena, affecting filings from China and the United Kingdom. As the end of both periods of extraordinary filings has already been reached in 2022, the quarterly filings time series were filtered and used in the VAR model, after removing the excess of China and UK filings from the normal trend.

Quarterly confidence indicators are obtained as a simple average of the correspondent three-monthly indicators after standardisation following equation 3.

As the purpose of the VAR model is to obtain forecasts of EUTM and RCD filings conditional on the European Commission (EC) DG-ECFIN forecasted values of NA indicators that are available in the AMECO database at annual frequency, the Denton method([27]) is applied to derive quarterly estimates from annual data. The application of the Denton method requires quarterly indicators, and they are taken from Quarterly National Accounts (QNA) published by Eurostat.

3.3 Selection of VAR model

The forecasting model proposed should be as simple as possible, consistent with economic theory and making the most of all available data as endogenous variables. The number of parameters of VAR models increases with the number of variables and lags so that only a few variables can be included, otherwise exhaustion of degrees of freedom results in inaccurate estimations and imprecise forecasts. The list of relevant variables, as explained in sub-section 3.2, includes: EUTM and RCD filings, domestic demand (including and excluding inventories), GFCF, NFCF, private FCE, net capital transactions with the RoW, confidence indicators for industry and service sectors and consumer confidence indicator. Both of the two filings time series and all three confidence indicators are included in all VAR models, but only some of the six NA indicators are included in the different VAR models to apply the parsimony principle and to avoid multicollinearity problems.

Table 1 shows summary statistics of 10 VAR models estimated with different combinations of variables. Each column corresponds to a different model and it includes the R^2 statistic for each of

([27]) The Denton method is recommended for benchmarking in the Eurostat Handbook on quarterly national accounts: https://ec.europa.eu/eurostat/documents/3859598/5936013/KS-GQ-13-004-EN.PDF/3544793c-0bde-4381-a7ad-a5cfe5d8c8d0?t=1613384318811.

the equations in the model; Final Prediction Error (FPE); Akaike Information Criteria (AIC); Schwarz-Bayes Information Criteria (SBIC); number of lags (decided based on FPE, AIC, SBIC, Hannan-Quin Information Criteria (HQIC) and likelihood-ratio tests); number of parameters; tests of eigenvalue stability condition; Lagrange Multiplier test of residual autocorrelation; and Jarque-Bera normality test of residuals (results of the last three post-estimation tests with 95 % confidence level). Finally, as the purpose of the VAR model is the forecasting of the filings time series, the table shows the out-of-sample forecasting errors for EUTM and RCD filings in the first quarter of 2023 (1q2023).

The variables included in the VAR models were transformed with logarithms to stabilise the variance with the exception of net capital transfers from the RoW, which can take negative values. Additionally, all the variables required one regular difference to be stationary ($Y_t - Y_{t-1}$) and the VAR model based on differenced time series provided better results than a model based on levels. Forecasting in differences rather than in levels can provide some protection against changing mean levels of the variables and reduces instabilities, thereby improving forecasts accuracy. Its interpretation when differences are applied to variables in logarithms is also clear as it is an approximation to growth rates.

The Johansen Cointegration Test was applied, rejecting the presence of a cointegration relationship among all variables, suggesting that the VAR models are appropriate rather than Vector Error Correction models (VECM).

Table 1: VAR models diagnostic tests and forecasting errors

	Model 1	Model 2	Model 3	Model 4	Model 5
EUTM filings* (R^2)	0.6153	0.7853	0.6376	0.3968	0.6623
RCD filings* (R^2)	0.3858	0.7432	0.4266	0.1930	0.4502
Confidence Industry (R^2)	0.3577	0.6803	0.3807	0.3489	0.3860
Confidence Services (R^2)	0.2334	0.5585	0.2752	0.2081	0.2842
Confidence Consumers (R^2)	0.4267	0.7287	0.4359	0.3715	0.4387
Private FCE (R^2)		0.7546	0.4310	0.2554	0.4504
GFCF (R^2)			0.3650		0.3773
NFCF (R^2)				0.5604	
Domestic Demand except inventories (R^2)					
Domestic Demand (R^2)					
Net Capital transactions RoW (R^2)					0.2223
FPE	4.72e-13	2.37e-13	1.02e-13	1.38e-15	6.73e-13
AIC	-14.2034	-12.6647	-10.0809	-14.3563	-5.3836
SBIC	-12.5290	-5.6992	-6.8848	-12.6643	-1.2438
Number of lags (p)	2	6	2	1	2
Number of parameters	11*5	37*6	15*7	8*7	17*8
Stability test	OK	OK	OK	OK	OK
No residual autocorrelation**	1	NO	2	NO	2
Normality test***	NO	1;5	1;2;5	2;5;6	1;2;5;6;8
Number of observations	77	73	77	78	77
Forecasting errors (%) 1q2023	3.0 / -1.3	4.7 / 4.5	2.5 / -1.6	4.7 / -1.5	0.4 / -0.2

	Model 6	Model 7	Model 8	Model 9	Model 10
EUTM filings* (R^2)	0.6533	0.6346	0.3869	0.6592	0.6427
RCD filings* (R^2)	0.4513	0.4402	0.1582	0.4626	0.4120
Confidence Industry (R^2)	0.4939	0.3586	0.3591	0.3634	0.3887
Confidence Services (R^2)	0.4292	0.2355	0.1807	0.2402	0.2581
Confidence Consumers (R^2)	0.4977	0.4282	0.3705	0.4301	0.4327
Private FCE (R^2)	0.4466				
GFCF (R^2)					
NFCF (R^2)	0.5985				
Domestic Demand except inventories (R^2)		0.4190		0.4444	
Domestic Demand (R^2)			0.0785		0.3536
Net Capital transactions RoW (R^2)	0.5985			0.2274	0.2140
FPE	3.37e-15	2.87e-13	1.23e-12	1.73e-12	3.02e-12
AIC	-10.6794	-11.8723	-10.4027	-7.2542	-6.6976
SBIC	-6.5397	-10.9226	-9.1337	-4.0581	-4.0581
Number of lags (p)	2	2	1	2	2
Number of parameters	17*8	13*6	7*6	15*7	15*7
Stability test	OK	OK	OK	OK	OK

No residual autocorrelation**	NO	2	1	NO	NO
Normality test***	1;2;5;6;8	1;2;5	2;5;6	1;2;5;7	1;2;5;6;7
Number of observations	77	77	78	77	77
Forecasting errors (%) 1q2023	0.7 / -0.1	2.7 / -1.4	4.7 / -1.6	0.4 / 0.1	1.1 / 0.5

Source: Author's own calculations with Stata program. All VAR models are based on time series data for the period 1q2002 to 1q2023 except out-of-sample forecasting error 1q2023 that excludes this quarter.
*times series filtered from extraordinary events in filings from China in the period 2020-2021 and the United Kingdom impact of the UKs withdrawal from the EU before 2016.
**Lagrange Multiplier residual autocorrelation test legend: NO if null hypothesis of no autocorrelation is rejected, YES if null hypothesis is not rejected at all lags until p, and number N when the null hypothesis is not rejected for N lags but it is rejected for the other lags tested, with 95 % confidence level.
***Jarque-Bera Normality test legend: NO if no residual in the model follows a Normal distribution and numbers indicate the order variable that are distributed Normally, with 95 % confidence level.

Based on Table 1, the VAR model with the best information criteria and FPE is model 4 including private FCE and NFCF and with only one lag. Nevertheless, model 6, adding the net capital transactions with the RoW to the variables in model 4 and two lags, also shows good results for FPE, much better coefficients of determination (R^2) especially for the filings time series and significantly improved forecasting errors in 1q2023 at the cost of reduced degrees of freedom. Due to the importance of this economic indicator with the continued deployment of RRF until 2024, and the fact that the objective of the VAR model is forecasting filings but not the economic indicators, model 6 is preferred. Nevertheless, in future years the realisation of the implementation of RRF included in EC forecasts should be checked and forecasts with and without this variable should be compared.

3.4 Granger causality and Impulse Response analysis of VAR model (28)

VAR models represent the relationship among a set of variables, but they are often used to analyse only certain aspects of the relationship among variables of interest. In our example, the VAR model estimated is based on eight variables although its main interest is to obtain forecasts for two of them: EUTM and RCD filings.

The chosen VAR model 6 in section 3.3 can be used to generate quarterly forecasts of both EUIPO filings time series as will be explained in section 4. Additionally, the economic relationships derived

(28) Details on Granger causality, Impulse Response and VAR models methods can be found in Lütkepohl, H. (2006).

from the chosen model are examined, based on the concept of Granger causality and the Impulse Response analysis.

Granger has defined a concept of causality that is easy to implement in the context of VAR forecasting models. The idea is that a cause cannot come after the effect. Thus, if a variable X affects ('causes') a variable Y, the former should help to improve the predictions of the latter variable. In other words, if Y can be predicted more efficiently if the information in X is taken into account, then X Granger causes Y.

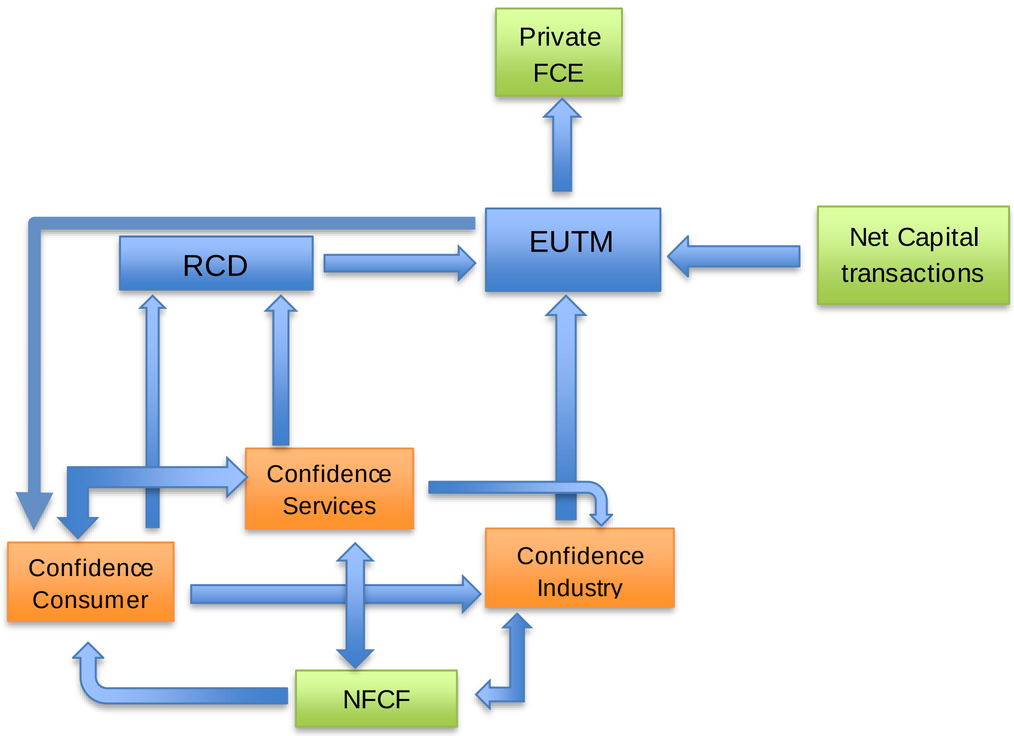
Let's represent (Granger) causality by an arrow:

$$X \longrightarrow Y$$

(X causes Y)

The Granger causality Wald test was applied to model 6 and figure 11 represents all Granger causality relationships that are significant at the 95 % confidence level.

Figure 11: VAR model 6 Granger causality diagram.



Source: Author's own calculations. Arrows represent significant Granger causality Wald test with 95 % confidence level. Legend: Filings series in blue, NA economic indicators in green and confidence indicators in orange. The direction of the arrow represents the Granger-causal relationship: an arrow from X to Y means that X Granger causes Y and so its present and past values are useful for prediction of Y.

Granger causality relationships can be summarised as follows.

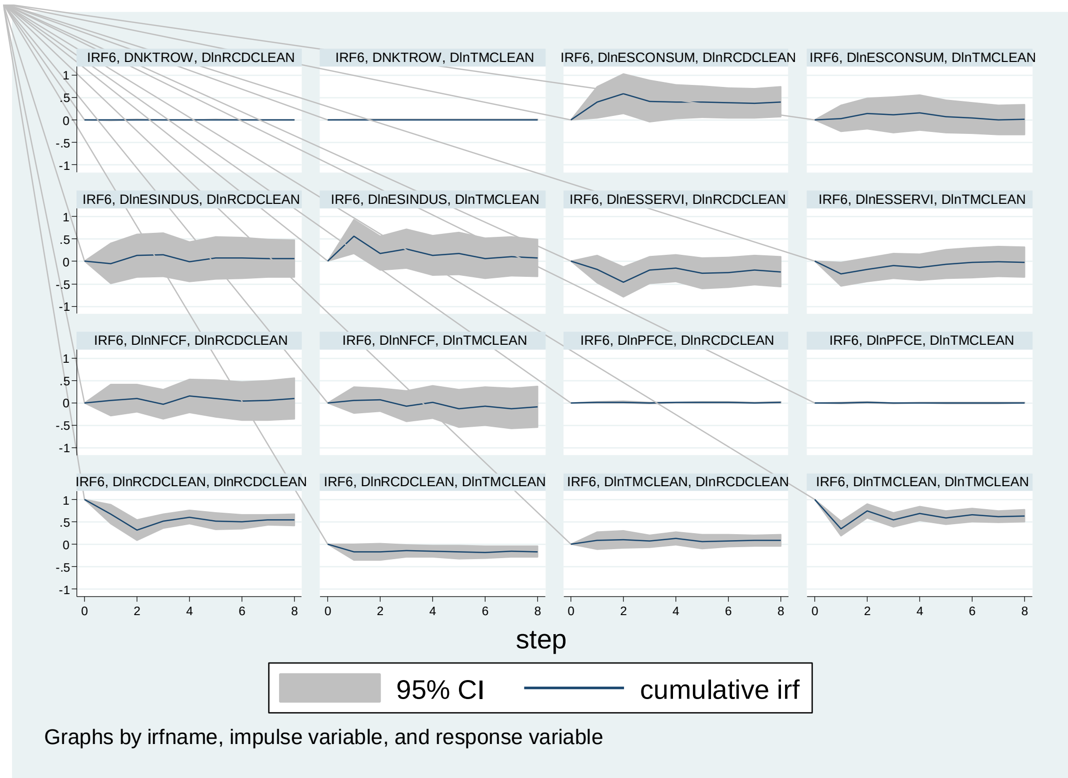
- EUTM filings are Granger caused by RCD filings, confidence indicator from industry sector and net capital transactions with the RoW and, in turn, they Granger cause private FCE and consumers' confidence.

- RCD filings are directly Granger caused by consumers and service sector confidence indicators and Granger cause EUTM filings. Also, private FCE Granger causes RCD filings with a 92 % confidence level, justifying keeping this variable in the model to improve RCD filings forecasts.

Therefore, the only variable that does not directly improve EUTM and RCD filings forecasts is the NFCF but it helps to forecast the three confidence indicators for which there is no information on their expected future values, as will be explained in section 4. The bidirectional relationships between service sector and consumers confidence indicators as well as between the industry sector confidence indicator and NFCF could also be explained by common factors not included in the VAR model.

In addition to the diagram of Granger causality, the influence of each variable on the future development of other variables in the system can be analysed based on the Impulse Response Function (IRF). The IRF of a VAR model describes the evolution of a model's variable in reaction to a shock in one or more variables. In Figure 12, only responses on EUTM and RCD filings are shown and IRFs are cumulative so that each graphic shows the response to a unitary shock of one impulse variable and its accumulated impact for eight quarters. For instance, the third graphic identifies the impact of a shock of one unit of the consumers' confidence indicator in the RCD filings rate of growth. The first value is the impact in the first quarter (t+1), the second one is the sum of the impact in the first and second quarter (t+1 and t+2) and so on, so that the eighth value is the accumulated impact in RCD filings after 2 years. The graphics also include the confidence intervals (CI) for the impact in each period, with 95 % confidence level.

Figure 12: Cumulative Impulse Response Function (IRF): impact on EUTM and RCD filings and confidence intervals.



Source: Author's own calculations with Stata, all variables are expressed in logarithm (except net capital transactions) indicated with 'ln' and one regular difference, 'D'.
Legend: RCDCLEAN and TMCLEAN = transformed RCD and EUTM filings as explained in section 2; NKTROW = net capital transactions with RoW; ESCONSUM = consumers' confidence indicator; ESINDUS = confidence indicator of the industry sector; ESSERVI = confidence indicator of service sector; NFCF = net fixed capital formation and PFCE = private final consumption expenditure.

As shown in figure 12, the variable with the greatest impact on EUTM filings is the confidence indicator for the industrial sector with a significant initial shock in the first quarter followed by a negative impact in the second quarter but still a significant cumulative effect after 2 years. With regards to RCD filings, consumers' confidence shows the greatest positive impacts in quarters 1 and 2 followed by small negative impacts from quarter 3 onwards and a cumulative impact after 2 years of the same size as the initial effect.

Based on this, section 4 will explain how the VAR model can be used to obtain quarterly forecasts based on known data on filings and confidence indicators as well as the forecasted values for NFCF, private FCE and net capital transactions with the RoW.

4 Conditional forecasts

As shown in equation 2, the VAR model expresses each variable as a combination of present and past values of itself and all other variables in the model with p lags. For the forecasting of time series based on a VAR model, the same equation is applied, and predictions substitute unknown values if necessary.

For example, equation 4 represents the prediction based on model 6 for the period t+4, which means four quarters after the current period (t).

Equation 4: Four quarters ahead forecasts of variable i based on model 6.

$$\hat{Y}_{i,t+4} = f(\hat{Y}_{1,t+3,}\ \hat{Y}_{1,t+2}, \hat{Y}_{2,t+3,}\ \hat{Y}_{2,t+2}, \dots \hat{Y}_{8,t+3,}\ \hat{Y}_{8,t+2})$$

where forecasted values of variable i m quarters ahead (t+m) are represented by $\hat{Y}_{i,t+m}$.

Based on model 6 with eight endogenous variables and two lags, equation 4 represents the forecasts, four periods ahead, as a function of all variables in the two previous periods: t+3 and t+2.

Then, the forecasting of EUTM and RCD filings four periods ahead based on VAR(2) are based on the predicted values of all the variables that could be obtained from the correspondent equations of the VAR model. Nevertheless, if the future values of some of the variables included in the model are known or forecasts are obtained from external sources, the VAR model can be run, including those expected values, to generate conditional forecasts.

Predictions of the NA indicators (NFCF, private FCE and net transactions with the RoW) are available in the AMECO database for years t+1 and t+2. The annual time series are transformed into quarterly series based on the Denton method and used as known values for the prediction of EUTM and RCD filings.

5 Conclusions and suggestions for further research

This paper aims to add to the current state of knowledge of IP economics by analysing the recent behaviour of European trade mark and design filings. The analysis of the evolution of filings in the last 3 years showed that some events that distorted their trends should be taken into consideration for forecasting purposes, otherwise the predictions based on excessive filings, that do not reflect the real economic situation in the EU market, will be inaccurate.

Multivariate models add to the univariate analysis the economic relationships of IPR filings as indicators of the confidence in the internal market. Then, forecasts are conditional on expected results of domestic demand variables as predicted by the EC DG-ECFIN.

The fact that EUTM filings are Granger caused by RCD filings confirms previous findings of overlapping of both types of IPRs and should be further researched, including additional IPRs.

The VAR model showed how confidence indicators can help to improve IPR filings forecasts and the analysis also confirmed that trade mark filings are more impacted by confidence in the industry sector while design filings respond more to consumers' confidence. A final interesting finding is that EUTM filings could be seen as a leading indicator for private consumption.

Future research on national filings could confirm the results presented in this paper, especially the usefulness of EUTM filings as a leading economic indicator due to the prompt availability and easy accessibility of this data, compared with other economic indicators.

References

- Abad A. and Quilis E.M (2004). Program for Cyclical Analysis <F> <G> <FDESC>. Users' guide.
- Baxter M, Kouparitsas M.A. (2005). Determinants of Business Cycle Co-movement: A Robust Analysis. Journal of Monetary Economics.
- Cristobal A. and Quilis E.M. (1994). Tasas de variación, filtros y análisis de la coyuntura. Boletin Trimestral de Coyuntura nº52, INE.
- European Central Bank (ECB) (2020). How to estimate a VAR after March 2020. ECB Working Paper Series No 2461.
- European Commission Directorate-General for Economic and Financial Affairs (DG-ECFIN) and Eurostat (2003). VAR modelling of the euro area GCD on the basis of principal components analysis. Sdrakas, N. and Viguie, C.
- European Commission, Directorate-General for Economic and Financial Affairs (DG-ECFIN) (2023). European Economic Forecast, Spring 2023. Institutional paper 200.
- European Patent Office (EPO) and European Union Intellectual Property Office (EUIPO) (2022). IPR-intensive industries and economic performance in the European Union. Industry-level analysis report, fourth edition.
- Eurostat (2013). Handbook on quarterly national accounts.
- International Monetary Fund (IMF) (2015). Forecasting the nominal Brent oil price with VARs. One model fits all? IMF Working Paper, Beckers, B. and Beidas-Strom, S.
- Lütkepohl, H. (2006). New introduction to multiple time series analysis. Springer.
- Maravall A. and Gomez V. (1997). Guide for using the programs TRAMO and SEATS. Banco de España, Servicio de Estudios. Documento de trabajo nº 9805.
- Organisation for Economic Co-operation and Development (OECD) Guay, A. and Pelgrin, F. SVAR models and the short-run resilience effect.
- Organisation for Economic Co-operation and Development (OECD) (2012) System of Composite Leading Indicators.
- Stemler, T. (2021). Forcing creativity: an analysis of Chinese IP subsidies and how they should be assessed under existing international trade agreements, Cybaris ®, Volume 12, Issue 2, Article 2.

- United States Patent and Trademark Office (USPTO), 2019. Innovation activities and business cycles: are trademarks leading indicators?
- United States Patent and Trademark Office (USPTO), 2021. Trademarks and patents in China: the impact of non-market factors on filing trends and IP systems.

List of Tables and Figures

Tables

Figures

MODELLING AND FORECASTING EUROPEAN TRADE MARK AND DESIGN FILINGS