Title: Trademark filings and patent application count time series are structurally near-identical and cointegrated: Implications for studies in innovation

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Abstract:

Through time series analysis, this paper empirically explores, confirms and extends the trademark/patent inter-relationship as proposed in the normative intellectual-property (IP)-oriented Innovation Agenda view of the science and technology (S&T) firm. Beyond simple correlation, it is shown that trademark-filing (Trademarks) and patent-application counts (Patents) have similar (if not, identical) structural attributes (including similar distribution characteristics and seasonal variation, cross-wavelet synchronicity/coherency (short-term cross-periodicity) and structural breaks) and are cointegrated (integration order of 1 – I(1)) over a period of approximately 40 years (given the monthly observations). The existence of cointegration strongly suggests a “long-run” equilibrium between the two indices; that is, there is (are) exogenous force(s) restraining the two indices from diverging from one another. Structural breakpoints in the chrono-dynamics of the indices supports the existence of potentially similar exogeneous forces(s), as the break dates are simultaneous/near-simultaneous (Trademarks: 1987, 1993, 1999, 2005, 2011; Patents: 1988, 1994, 2000, and 2011). A discussion of potential triggers (affecting both time series) causing these breaks, and the concept of equilibrium in the context of these proxy measures are presented. The cointegration order and structural co-movements resemble other macro-economic variables, stoking the opportunity of using econometrics approaches to further analyze these data. As a corollary, this work further supports the inclusion of trademark analysis in innovation studies. Lastly, the data and corresponding analysis tools (R program) are presented as Supplementary Materials for reproducibility and convenience to conduct future work for interested readers.

Keywords: trademarks, patents, innovation, indicator, I(1), cointegration, breakpoint, wavelet, time series

Disclosures and Disclaimers:

The author is an employee of Takeda Pharmaceuticals; however, this work was completed
Introduction

One of the more common methods for inquiring about the dynamics (e.g., rates, structure) of innovativeness in science and technology (IS&T) firms is via intellectual property (IP)-related metrics (Dziallas and Blind, 2018). Simplistically, the rationale of using IP-related proxy measures of innovation primarily rests on the nature of the output (viz., inventions) generated by such firms (Daizadeh et al., 2002). Notably, sponsors may seek one or more patents to protect an invention, assuming such IP meets certain evidentiary standards of utility, novelty, and non-obviousness and perceived future economic rents justify a patent over that of publishing or retaining the knowledge as a trade-secret (ibid). Therefore, one can understand the intrinsic concept captured in a patent, and that the greater number of such IP assets implies greater innovativeness. Optimizing IP generation (and thus innovativeness) has resulted in S&T firms reorienting their organizations, systems, and processes accordingly (Daizadeh, 2003, 2007).

Conceptually, it is more challenging to extend the logic of innovativeness to other forms of IP, especially to that of trademark-related metrics (e.g., filings) of IS&T firms, as the criteria for meriting a trademark is a more amorphous entity, generally defined as ‘word, phrase, symbol, and/or design that identifies and distinguishes the source of the goods of one party from those of other1.’ Some researchers have expressed significant concern over the use of trademarks of IS&T firms. For example, Hipp and Grupp (2005) state “even services containing no or only low levels of innovation can be brand protected. This limits the trademarks statistics’ value as an innovation indicator (ibid, p 526).” Others have been more nuanced with their criticism of the approach, considering the topic as one of definition (Flikkema et al, 2019).

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1 [https://www.uspto.gov/trademarks-getting-started/trademark-basics/trademark-patent-or-copyright](https://www.uspto.gov/trademarks-getting-started/trademark-basics/trademark-patent-or-copyright) viewed on 19-Nov-2019.
and are leveraging relatively recent research viewing the link between trademarks and innovation accordingly. For exhaustive accounts on the literature on such topics, readers are referred to Dziallas and Blind (2019), Siekierski, et al., (2018), among others.

In the past, among other interesting metrics, Daizadeh (2007, 2009) found strong (>96%; p-value < 0.0001) correlation between patent applications (Patents) and trademarks filings (Trademarks) over a multi-year (1970-2002) period. In the same work, Daizadeh also proposed that the normative model, termed herein the 'Daizadeh Innovation Agenda (DIA)' (see Figure 1 in Daizadeh, 2009), which was conjectured from the legal and financial nature of patents, trademarks, publications, and press releases, may help in understanding the identified correlative patterns. The Innovation Agenda, as proposed, is to be comprised of several socio-economic S&T firm-specific metrics including: US Research and Development Spend, Number of Trademark Filings and Registrations, Number of Patent Applications and Issuances, Number of Press Releases, and various S&T related Stock Indices. While the data used (as is here) is US specific, it may be generalizable to any intellectual-property based entrepreneurial S&T intensive jurisdiction. In that work, Daizadeh found – using annual values for these metrics and based on correlation and partial-correlation analysis – a series of interesting findings including correlation and partial correlation across these selected metrics.

Lastly, the use of Trademark data in innovation studies has been of recent interest. Daizadeh (2007, 2009) added empirical support for the conjecture that if Patents were a proxy measure of innovation, and if Trademarks were strongly correlated with Patents, then Trademarks may also play a role as a proxy measure of innovation. Recently there has been renewed interest in the use of Trademarks (and related data) as measures of innovation (see, e.g., citations in Dziallis and Blind, 2019). Characterizing the inter-relatedness between these metrics beyond that of correlation may further strengthen the argument that Trademarks be a standard measure of innovativeness in S&T firms.
Time series statistical analysis is prevalent across scientific disciplines and includes a diverse assortment of approaches. Statistical practices of relevance to this paper, as we seek to understand the temporal co-mobility (inter-relatedness) of Patents and Trademarks (bivariates), include descriptive statistics (e.g., seasonal variation), cointegration, structural break / change point, and cross-wavelet analyses. While several approaches may have been taken to investigate inter-relatedness of a bivariate system, the methods described below were selected due to several factors including: ease of access, ease of interpretation, prevalence of use (and thus greater confidence in strength and limitations of methods), and intrinsic criteria of data (e.g., non-normality).

Various descriptive statistics were performed to provide insight into the distribution (e.g., normality) and stability (e.g., stationarity), and to better select further statistical analyses. As previously mentioned, Daizadeh (2007, 2009) found a strong correlation between Patents and Trademarks. Using time series decomposition and cross-wavelet analyses, as a qualitative tool, the nature of the correlation (synchronicity) was further explored including elucidating periodicity contributing the most to the correlation pattern. This work empirically explores monthly observations over a period of roughly 40 years for both time series. Generally, this report finds that Trademarks and Patents (time series) are similar statistical moments (mean, variance, skew, and kurtosis), non-normal and non-stationary with seasonal variation, with short-term periodicity, across all years explored. A cross-wavelet analysis was also performed to obtain a view into latent periodicity. The analysis reconfirmed the high correlation but resolved interesting dynamics in short-term periodicity associated over the most recent decade.

Cointegration (unlike correlation) analysis captures so-called ‘long-run equilibrium’ derived from stochastic relationships restricting co-movement divergence between the timeseries under-study (Granger, 1981; Engle and Granger, 1987; Dolado, et al., 1999). That is, cointegration regards the degree...
of differences in the timeseries as opposed to the directionality of the co-movement (e.g., positive correlation in which the bivariates move in the same direction). The cointegration statistical analyses, included those of the Johansen and Philips and Ouliaris tests, confirmed that the time series were co-moving, implying that some exogeneous effect(s) were imposing a constraint on this system.

As other statistics, cointegration may be affected by a non-trivial change in the course of the timeseries, which may be termed a ‘structural break,’ ‘structural change,’ or a ‘regime shift.’ While there are several definitions for a structural break, and thus methods to elucidate or predict such changes, the following is illustrative: “Structural break as an unpredictable event in which the relationship among the variables in a model changes, and this change cannot be predicted in any sense from past data (Maheu and Gordon, 2008).” Should such abrupt changes occur (quasi)-simultaneously, then it may be presumed that the same exogeneous event affects both Trademarks and Patents, adding further (if not confirmatory) evidence of not only inter-relatedness between the variables. Here, it is found from generalized fluctuation tests that structural breaks exist and identify and date the breakpoints as: Trademarks: 1987, 1993, 1999, 2005, 2011; Patents: 1988, 1994, 2000, and 2011, using standard models (see below for details and associated citations). A discussion of potential triggers for these dates is presented below.

In this paper, assuming the DIA model for the IP-intensive S&T firm, the base hypothesis explored is that if Patents and Trademarks are both affected by the same and/or similar exogenous variables, then their respective timeseries should be ‘inter-related.’ Further, these data add support to an assumption proposed in the DIA; namely, that an exogeneous factor(s) was applied to patent applications and trademark filings, leading to the inter-relationship. Bivariate inter-relatedness is explored empirically using descriptive statistics, structural break point, and cointegration analyses on the bivariate monthly
timeseries over an extended period (1977-2016; see Methodology) compared with the original Daizadeh paper. Observation of simultaneous/quasi-simultaneous structural changes, existence of cointegration (which would imply a ‘long term equilibrium’ restraining the differences between the timeseries), and other structural co-movements (such as synchronicity, coherence) in the bivariate timeseries would support the theory that common (or similar) exogeneous factors exist, and thus further add additional supportive evidence to DIA theory (necessary for formalizing further study), as well as illustrates the import of trademarks to the innovation process and thus to IS&T firms generally (see Results). This manuscript concludes with a discussion of the assumptions and limitations of the approach, and avenues for future development.

All datasets and the R Program script is presented in the Supplementary Materials section of this manuscript for reproducibility and convenience to conduct future work. Interested readers are strongly encouraged to either try their own approaches to investigate the structure of the bivariate timeseries with or without considering the materials provided.

**Methodology:**

*Data sources and preparation:*

The data were comprised of the monthly number of US patent applications (Patents) and the monthly number of US trademarks filings (Trademarks) from 1977 to 2016.

*Number of patent applications and trademark filings:* The data on Patents and Trademarks were obtained from the respective publicly available websites supported by the United States Patent and Trademark Office (USPTO) as described below:

| Variable | USPTO Publicly Available Search Site | Search Characteristics* |
|----------|--------------------------------------|-------------------------|
| Patents  | [http://patft.uspto.gov/netahml/PTO/search-adv.htm](http://patft.uspto.gov/netahml/PTO/search-adv.htm) | Application Filing       |
Two searches were manually executed, resulting in 472 datapoints for each variable and captured in Excel for import into R. The 472 datapoints for each variable represents monthly observations over the period of study (approximately 40 years). The data is presented in the Supplementary Materials section of the manuscript for ease of reference and for the sake of reproducibility.

**Statistical Analysis.**

Methodology followed standard implementation, and default parameters were used throughout. While the R code (R Core Team, 2019) is presented in the Supplemental Materials section of this manuscript for reproducibility, the general algorithm for the analysis is as follows:

- Load bivariate timeseries, identify and replace outliers with average of prior and posterior-month values (R package ‘tsoutliers’ (López-de-Lacalle, 2019). Note: 3 outliers were determined for Trademarks (September 1982; November 1989; and June 1999) and 4 for Patents (September 1982, June 1995, October 2007, and March 2013).
- Decompose data and perform descriptive statistics, including deriving kurtosis, skew (R package ‘moments’ (Komsta and Novomestky, 2015)), nonparametric (Spearman and Kendall) correlation coefficients (ibid), and cross-wavelet analyses (R Package ‘biwavelet,’ (Gouhier, et al. 2019)) on full timeseries.
- Test for structural breakpoints (SBPs) using empirical fluctuation processes (R package ‘strucchange’ (Zeileis, et al., 2002, 2003)): 
Results:

Descriptive Statistics:

The distributions of the two time-series were similar (e.g., approximately symmetric (skew) and platykurtic) and thus no transformation was performed on the data (Table 1). The respective trends of the time-series generally evolve in time in an ‘exponential manner,’ both have similar per-annum quarterly seasonal effects, with increased contributions from the stochastic (random) elements post-2010, with a spike at circa 2000 and circa 1995 for Trademarks and Patents, respectively (Figures 1 and 2). Qualitatively it would seem that Trademarks present somewhat greater degree of ‘randomness’ than Patents.

< Insert Table 1, Figure 1, and Figure 2 here.>

Caption table 1: Descriptive statistics of Trademarks and Patents
Correlation and Cross-Wavelet Analysis

Spearman and Kendall analysis finds a strong coefficient of correlation of 0.94 and 0.80, respectively, between Trademarks and Patents; this reconfirms the work of Daizadeh (2007, 2009) for an extended period of time (1977-2016). Further examination using cross-wavelet analysis shows broadly high to very high (1) coherency (red to dark-red splotches) across the Trademark/Patent spectra and periods. Relatively low periods post-1995 and more uniformly post-2002 demonstrate increased bivariate synchronicity (at 5% statistical significance).

Existence, testing, and Dating of Structural Break points, and subsequent segmenting of the timeseries:

The empirical fluctuation processes (EFPs) (ordinary least squares (OLS) and recursive modeling (REC)) test the null hypothesis of “‘no structural change’ [which] should be rejected when the fluctuation of the empirical processes gets improbably large compared to the fluctuation of the limiting process (Zeileis, et al., 2002, p. 6).” The EFPs were executed with a significance criterion (alpha) of 5%. The results of these four tests for Trademarks are presented in Figure 4; a similar result was found for all tests for Patents (figure not shown but calculations may be reproduced in the Supplemental Materials). Significance testing for the existence of SBPs are presented in Table 2, with p-values less than or equal to 0.01.

As can be seen in either of Figures 4 and Table 2, the EFPs cross the critical value boundary, and therefore rejecting the null hypothesis of no SBP at the 5% level. Further, the complex structures for
both (Approvals and Guidances) timeseries across the tests suggest multiple structural breakpoints (Zeileis et al., 2005).

< Insert Figure 4 and Table 2 here. 

Caption Figure 4: Existence of structural breakpoints for Trademarks:

Caption Table 2: Significance testing (p-value) for the existence of structural breakpoints in Trademarks and Patents>

**Dating of structural breakpoints**

The general idea of the Bai-Perron dynamic programming algorithm to date the structural breakpoints is to elucidate the breakpoints through minimizing the residual sum of squares of a linear regression model (additional details may be found in Bai and Perron, 2003 and Zeileis, et al., 2003). SBPs (including confidence limits) are presented in Figure 5 and in Table 3.

< Insert Figure 5 and Table 3 here. 

Caption Figure 5: Structural breakpoints with corresponding confidence intervals (see Table 3) identified in Trademarks (black) and Patents (red)

Caption Table 3: Dating (via Bai-Perron) of the structural break points in Trademarks and Patents >

The data suggests several segments in which there is no abrupt changes in the intrinsic variability of the timeseries (stationarity). Thus, several time segments of stationarity were elucidated, and affords an ease in further analyses given minimal statistical variance/fluctuations. The existence of stationarity during these periods of time strongly suggests the lack of strength of any exogeneous factor (e.g., promulgation of novel legal frameworks and/or technologies) on the time-course of these variables. Thus, the heuristic was defined to be the longest time between Trademarks and Patents structural break points (Table 4); 6 such time-segments were identified and used for the rest of the analysis.
Cointegration and the maximum order of integration (I(d)):

Results for the Johansen Procedure and Phillips and Ouliaris tests demonstrated cointegration at alpha \( \leq 1\% \) for the full bivariate timeseries and the third-, fifth-, and sixth-time segments. The size of the test statistic is notable for both tests across the full timeseries (Table 5).

Discussion and Conclusion:

The DIA model offers a formal normative scaffold to explore variables of interest to innovation on the company, sector, industry, or national basis for science and technology firms with a specific focus on securing economic rents from specific forms of IP (notably, patents and trademarks) and their communication and subsequent monetization (Daizadeh, 2007, 2009, 2006, 2007b). While inquiries into the DIA model were restricted to only broad correlation analysis and a specific case study, additional work is needed to further validate the model. Importantly, this additional work may also provide insights into metrics investigating innovative productivities of firms.
Specifically, the DIA model suggests an inter-relationship between various metrics. Here, the inter-relationship between trademark filings (Trademarks) and patent applications (Patents) are explored using a set of statistical analysis that seek to empirically identify structural similarities between the temporal evolution of Trademarks and Patents. The descriptive analysis demonstrated that the distributions of the timeseries are similar. Correlation and cross-wavelet analysis clearly showed synchronicity and coherence between the timeseries. Cointegration analysis demonstrates a ‘long-run’ equilibrium (restricting divergence) has been established between the timeseries.

The DIA model proposes that R&D expenditure is a driver in patent and trademark originations. This is consistent with the time series (cointegration) analysis performed by Verbeek and Debackere (2006). These authors find “patent evolution is strongly related to ... levels of public and private R&D expenditure... (see abstract and conclusions in ibid).”

With regards to the dating of structural breakpoints in the bivariate time series, while additional statistical work is required to better understand sensitivity (as different approaches may realize different dates), it is challenging to link economic shocks that may have caused the abrupt concomitant temporal perturbations to the dates of simultaneous / near simultaneous shocks in the bivariate time series (viz., 1988, 1993/1994, 1999/2000, and 2011). For example, one can hypothesize (and therefore test) that domestic economic hardships affecting R&D (e.g., the dot-com crisis) or the end of a bull market may have been a direct or contributing factor to the abrupt temporal changes in the IP-assets of S&T firms such as Patents and Trademarks (see, e.g., Bleoca, 2014; ). Simultaneously, one can also hypothesize that there was an ‘event’ associated with the start of the recent “bull market” over the last decade that may have been initiative in the early 2010’s (potentially irrespective of or in addition to fluctuations in the legal landscape (notably, from a patent perspective, the ‘Leahy-Smith America
Further work would need to be done to examine such causal factors during the years identified in this work.

Lastly, from a conceptual perspective, the “long-run” equilibrium of R&D expenditure spill-over effects such as IP-related assets (Trademarks and Patents) and the equilibrium (stationary) processes elucidated between the structural breakpoints (herein called ‘regimes’ – see Table 4) may be recast along the lines of Schumpeter’s theory of business cycles and more generally innovation theory. From this work, while there may be abrupt discontinuations (assumed to be due to non-endogenous / exogenous factors) within short periods of time (approximately < 2 years), overall economic and innovative progress (as defined by several metrics including those of intellectual property) has continued during the relatively long-time course under-study (monthly intervals of over 40 years). The approach taken herein treats Trademarks and Patents as macro-socio-economic variables averaging across degrees (e.g., radical versus incremental), types (e.g., process versus product) and sectors (e.g., biotech versus manufacturing) of innovativeness. Aligned with Schumpeterian thought around business cycles, and in terms of cointegration of certain macro-socio-economic variables, Konstantakis and Michaelides (2017; page 20) note that “it is exactly upon the existence of this equilibrium relationship that Schumpeterian business cycles were founded, since progressive evolution of innovative activity expressed through technology, leads to the evolution of economic activity as a whole.”

Given the Results above, there is a strong and intimate inter-relationship exists between Trademarks and Patents. Beyond supporting the DIA model, this work thus adds to the emerging literature (beginning in part with Daizadeh, 2007) that Trademarks should be of interest as an innovation metric as a unique entity and/or in combination with other such metrics.

\[\text{Short Title: Timeseries analysis of trademarks filings and patent applications: Implications on Innovation}\]

\[\text{Invents Act’ that became law in 2011}^2\).

\[\text{https://www.govinfo.gov/app/details/PLAW-112publ29}\]
As with any statistical analysis, there are advantages and disadvantages as well as practical aspects (e.g., computational intensity or algorithm complexity) of the methodologies used within the constraints of the data collected (Daizadeh, 2020). Thus, multiple, complementary, and orthogonal methods to investigate the inter-relationship were used. For example, wavelet analysis is well-known to be of utility across a broad range of implementations (e.g., cross-wavelet) with non-stationary timeseries (Rhif et al, 2019) well complemented both the decomposition (notably seasonal effects) results and the correlation coefficient calculations; two different cointegration tests were performed: Johansen trace test (Johansen, 1988) and Phillips and Ouliaris test (Phillips and Ouliaris, 1990).

The analysis presented in this paper provide supportive evidence for a component of the DIA model as well as metrics tracking innovativeness, however, much further inquiries remain. Future experiments may include:

- Geography: e.g., ex-US versus US inter-relationship inquiries
- Additional trademark and patent variables: e.g., granted patents and designated trademarks
- Integration of additional DIA variables: e.g., numbers of press releases over time and financial metrics
- Deepened analysis: Mapping identified structural breakpoints to the introduction of promulgation of new/updated legal frameworks and/or new technologies to better understand impact
- Comparison of IP-metrics (e.g., trademarkmetrics/patentmetrics) to broader econometrics and scientometrics: e.g., comparing I(1) processes
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Figure 1: Timeseries decomposition of Trademarks
Figure 2: Timeseries decomposition of Patents
Figure 3: Cross-wavelet analysis of Trademarks and Patents; solid black contour lines designate the 5% significance
Figure 4: Existence of structural breakpoints for Trademarks
Figure 5: Structural breakpoints with corresponding confidence intervals (see Table 3) identified in Trademarks (black) and Patents (red)
Table 1: Descriptive statistics of Trademarks and Patents

| Variable  | Minimum | 1st Quartile | Median | Mean  | 3rd Quartile | Maximum | Standard Deviation | Skewness | Kurtosis |
|-----------|---------|--------------|--------|-------|--------------|---------|-------------------|----------|----------|
| Trademarks| 1895    | 5537         | 15456  | 15276 | 23574        | 37317   | 9418.054          | 0.202    | 1.76     |
| Patents   | 3134    | 7598         | 14468  | 13930 | 19422        | 30969   | 6523.347          | 0.185    | 1.76     |

Table 2: Significance testing (p-value) for the existence of structural breakpoints in Trademarks and Patents

| Variable  | OLS-CUSUM     | OLS-MOSUM | REC-CUSUM | REC-MOSUM |
|-----------|---------------|-----------|-----------|-----------|
| Trademarks| < 2.2e-16     | 0.01      | < 2.2e-16 | 0.01      |
| Patents   | < 2.2e-16     | 0.01      | < 2.2e-16 | 0.01      |

Table 3: Dating (via Bai-Perron) of the structural break points in Trademarks and Patents

|                  | Trademarks | Patents |
|------------------|------------|---------|
| 2.7% Breakpoint  | Feb 1987   | Jan 1998|
| May 1987         | Jul 1987   | Apr 1988|
| Jan 1993         | Mar 1993   | Dec 1993|
| Apr 1993         | Mar 1999   | Apr 1994|
| Oct 1998         | Dec 1999   | Feb 2000|
| Feb 2000         | Nov 2005   | Jul 2000|
| Oct 2004         | Feb 2011   | Apr 2010|
| Sept 2010        | Apr 2011   | Feb 2011|

Table 4: Segments identified as longest length of time between Trademarks and Patents structural break points (see Results for description)

| Segment | Heuristic: Longest time between Trademarks and Patents structural break points* |
|---------|--------------------------------------------------------------------------------|
| 1       | Sep 1977 to April 1987                                                          |
| 2       | Feb 1988 to Feb 1993                                                            |
| 3       | May 1994 to Dec 1998                                                            |
| 4       | Mar 2000 to Jan 2005                                                            |
| 5       | Mar 2005 to Jan 2011                                                            |
| 6       | Mar 2011 to Dec 2016                                                            |

*That is, the origin to the month prior to breakpoint: October 1983
Table 5: Results of cointegration tests across full bivariate timeseries and each time-segment

| Segment | Johansen procedure (trace statistics, without linear trend and constant) | Phillips and Ouliaris Test |
|---------|-------------------------------------------------------------------------|----------------------------|
|         | r<=1: Test statistic versus (v) critical value of test (at lowest level of alpha) | r=0 Test statistic versus (v) critical value of test (at lowest level of alpha) | Value of Test Statistic versus (v) critical value of test (at lowest level of alpha) |
| Full timeseries | 75.47 v 24.60 (1%) | 222.6575 v 55.1911 (1%) |
| 1       | 23.37 v 19.96 (5%) |  | |
| 2       | 36.34 v 24.60 (1%) |  | |
| 3       | 24.64 v 24.60 (1%) | 51.1519 v 40.8217 (5%) | |
| 4       | 9.95 v 9.24 (5%) | 74.61 v 24.60 (1%) |  |
| 5       | 11.58 v 9.24 (5%) | 83.56 v 24.60 (1%) | 83.8507 v 55.1911 (1%) |
| 6       | 33.83 v 24.60 (1%) | 54.1304 v 40.8217 (5%) | |

Table 6: Number of differences required to bring the time-series into stationarity.

| Variable   | Segment | KPSS | ADF | PP |
|------------|---------|------|-----|----|
| Trademarks | Full dataset | 1    | 1   | 1  |
| Patents    | 1       | 1    | 1   | 1  |
| Trademarks | 2       | 1    | 0   | 0  |
| Patents    | 1       | 0    | 0   |    |
| Trademarks | 3       | 1    | 1   | 1  |
| Patents    | 1       | 1    | 0   |    |
| Trademarks | 4       | 1    | 0   | 0  |
| Patents    | 0       | 0    | 0   |    |
| Trademarks | 5       | 0    | 0   | 0  |
| Patents    | 0       | 0    | 0   |    |
| Trademarks | 6       | 1    | 1   | 1  |
| Patents    | 0       | 0    | 0   |    |
### - Begin Supplementary Materials ###

**Trademarks**

Go to TESS: [http://tmsearch.uspto.gov/bin/gate.exe?f=tess&state=4804:57thz4.1.1](http://tmsearch.uspto.gov/bin/gate.exe?f=tess&state=4804:57thz4.1.1)

Manually search and collect Number of Trademarks as follows:

By Filing Date: "(198712$)[FD]" - Where 198712$ is the %Y%m$.

**Patents**

Go to PATFT: [http://patft.uspto.gov/netahtml/PTO/search-adv.htm](http://patft.uspto.gov/netahtml/PTO/search-adv.htm)

By Application Filing Date: "APD/12/$/2018"

The patent and trademark filings data were collected from Sept 1977 to Dec 2018.

Confirm version of R:

```r
> citation()
R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
```

```r
> version

```

```r

```

Read into R:

```r
> IP<- read.csv("C:/Users/DAIZAI/Desktop/patent/Patent-Trademark.csv", sep="",)
```

Confirm dataframe - length/variables and shrink by 24m to avoid so-called 'patent cliff':

```r
> str(IP)
```
Short Title: Timeseries analysis of trademarks filings and patent applications: Implications on Innovation

'data.frame': 496 obs. of 3 variables:
$ Date: Factor w/ 496 levels "1/1/1978","1/1/1979",..: 455 42 84 126 1 168 209 250 291 332 ...
$ Number.of.Trademark.Applications: int 2669 2597 2552 2604 2386 2370 3126 2738 3028 3088 ...
$ Number.of.Patent.Applications: int 5760 5898 5731 5064 5439 6660 5799 6487 6419 ...

# Shrinking by 24 months due to so-called "patent-cliff"
> TrademarksTotal<-IP$Number.of.Trademark.Applications[1:472]
> PatentsTotal<-IP$Number.of.Patent.Applications[1:472]

# Convert to Time-Series, decompose time-series, and perform descriptive statistics
> tsTrademarks<-ts(TrademarksTotal,start=c(1977,9),frequency=12)
> tsPatents<-ts(PatentsTotal,start=c(1977,9),frequency=12)

> tsTrademarks

Jan   Feb   Mar   Apr   May   Jun   Jul   Aug   Sep   Oct   Nov   Dec
1977  2669  2597  2552  2604
1978  2386  2370  3126  2738  3028  3088  2708  2638  2465  2793  2636
1979  2518  2350  2920  2968  2953  2794  2741  2829  2438  2956  2676
1980  2469  2607  3035  2893  3094  2883  2590  2928  4081  3412  3559
1981  3329  4113  3906  4297  3871  4358  4077  3815  3688  3879  4162
1982  3594  4009  5128  4868  5244  4942  5264  15843  1895  3126  3529
1983  3915  4224  4297  4389  4543  4192  4893  4265  4634  4189  4296
1984  4281  4472  5167  5068  4762  4837  4914  4803  4064  4896  4922
1985  4296  4408  5087  5417  5537  4914  5537  5215  4627  5218  4747
1986  4785  4677  5569  5153  5397  5630  5152  5715  4787  4950  4931
1987  4188  4826  5528  5780  5372  5860  6269  5990  5309  5624  5454
1988  4758  5756  5730  6518  6358  5706  5473  6341  5776  5899  5384
1989  5546  5761  6615  6230  7071  6496  5995  6567  6867  11400  8450
1990  9209  8797  10687  9936  9836  9707  9319  9634  8167  9567  8417
1991  7906  7986  9192  9734  9441  8962  9371  9260  8884  9073  8805
1992  7486  8612  10248  9940  8776  10078  10019  9701  9348  7853  8599
1993  9143  9143  11059  11352  10594  11897  11160  11628  11448  10374  11248
1994  9599  10388  12173  11664  12292  12902  10728  12536  11443  11932  11339
1995  10961  11857  14860  12391  14323  13644  12325  14434  12631  13726  12926
1996  12582  13872  15117  15636  15565  14433  15447  15590  15234  16299  14727
1997  14060  15229  16962  17079  16460  16465  16425  15363  16089  16901  14367
1998  13510  15465  17624  17224  15805  17862  17515  16270  16331  17426  16737
1999  16002  18431  22143  20957  20515  24106  21999  23891  22563  24753  24225
2000  23412  25815  30423  25204  26986  24831  21769  24626  21644  22962  20340
2001  19248  18923  20732  19781  20778  18551  18311  19608  14770  17727  15587
2002  16273  16357  18555  18946  19622  17734  18359  18958  17639  19111  16487
| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1977 | 5760 | 5898 | 5731 | 6630 |
| 1978 | 5064 | 5439 | 6660 | 5799 | 6487 | 6419 | 5671 | 5831 | 5697 | 6012 | 5756 | 6210 |
| 1979 | 5303 | 5240 | 6131 | 6071 | 6247 | 6087 | 5726 | 5999 | 5541 | 6459 | 5913 | 6399 |
| 1980 | 5492 | 5619 | 6491 | 5971 | 6292 | 6325 | 6077 | 5328 | 6143 | 6246 | 5414 | 6726 |
| 1981 | 4899 | 5351 | 6548 | 5857 | 5583 | 6377 | 5907 | 5539 | 5489 | 5726 | 5602 | 6354 |
| 1982 | 4677 | 5313 | 6793 | 5724 | 5702 | 6543 | 5894 | 5834 | 10870 | 3134 | 4604 | 5926 |
| 1983 | 4698 | 4900 | 6279 | 5451 | 5657 | 6202 | 5390 | 5621 | 5740 | 5648 | 5544 | 6507 |
| 1984 | 4940 | 5557 | 6360 | 6216 | 6391 | 6522 | 6033 | 6230 | 5708 | 6631 | 6319 | 6774 |
| 1985 | 5381 | 6111 | 6664 | 6807 | 6895 | 6257 | 6713 | 6290 | 6814 | 7204 | 6247 | 7251 |
| 1986 | 5730 | 6296 | 7137 | 7026 | 6837 | 6982 | 6994 | 6486 | 7150 | 7544 | 6200 | 7814 |
| 1987 | 5918 | 6753 | 7899 | 7633 | 7027 | 7852 | 7784 | 6968 | 7510 | 7814 | 7539 | 8614 |
| 1988 | 6315 | 7682 | 8992 | 7850 | 8040 | 8737 | 7843 | 8262 | 8551 | 8721 | 8082 | 9321 |
| 1989 | 7616 | 8117 | 9466 | 8379 | 9123 | 9378 | 8133 | 8702 | 8588 | 9083 | 8706 | 9308 |
| 1990 | 8151 | 8472 | 9707 | 9061 | 9197 | 9331 | 8963 | 9269 | 8533 | 10444 | 8128 | 9421 |
| 1991 | 7879 | 8270 | 9363 | 9413 | 9406 | 9080 | 9394 | 8954 | 9327 | 9737 | 9155 | 9704 |
| 1992 | 8237 | 8485 | 10025 | 9591 | 8881 | 10282 | 9822 | 8666 | 10009 | 9586 | 9180 | 10693 |
| 1993 | 8063 | 8728 | 11064 | 9963 | 9246 | 10500 | 9793 | 9531 | 10232 | 9904 | 10034 | 11401 |
| 1994 | 9243 | 9614 | 12007 | 10453 | 10893 | 12276 | 10303 | 11300 | 12499 | 11444 | 11444 | 13760 |
| 1995 | 10445 | 10716 | 13835 | 11945 | 17222 | 28123 | 8860 | 10340 | 11124 | 10913 | 11152 | 12746 |
| 1996 | 10346 | 11112 | 13067 | 12689 | 13000 | 13285 | 13677 | 13195 | 14326 | 14524 | 13319 | 15858 |
| 1997 | 13121 | 13531 | 15641 | 15287 | 15015 | 16286 | 15456 | 14815 | 16658 | 16871 | 14529 | 16885 |
| 1998 | 12722 | 13746 | 16543 | 15062 | 14511 | 16769 | 15660 | 14426 | 15607 | 15603 | 14861 | 18092 |
| 1999 | 12865 | 14204 | 17997 | 15791 | 15337 | 17893 | 15963 | 16308 | 17160 | 16447 | 16702 | 19417 |
| 2000 | 14586 | 16451 | 20021 | 15922 | 17884 | 19641 | 15521 | 18278 | 19273 | 17834 | 18532 | 19122 |
2001 16493 17127 17692 18593 20122 18202 19753 17856 19239 18210 19660
2002 17694 17281 20278 18963 19891 19568 19240 18754 19562 20034 17799 21302
2003 16740 16898 19990 18907 18242 19748 18830 17542 19825 19708 16896 22063
2004 15528 16931 21274 18212 16712 20593 17779 17943 19884 17521 18130 22102
2005 14968 17021 22490 18546 17987 21090 16914 18462 19787 17592 18133 22188
2006 14550 16931 22216 18212 17560 19240 18754 19568 19240 18754 19568 22766
2007 16930 17539 22271 18427 19480 20506 18797 20267 19143 25045 18195 21820
2008 16717 18825 21168 19762 19318 21035 19896 21495 21413 18120 23736
2009 15375 17696 21848 18816 17438 20736 19164 17736 20407 19603 18327 23801
2010 14972 17696 19786 20199 19019 22414 19760 19867 21604 20657 20612 25143
2011 17261 18992 25367 20428 20964 23822 20058 22268 26472 20658 21926 26522
2012 17222 19167 21736 22546 23921 25237 23054 24756 27051 22929 24437 27708
2013 18316 23728 42788 19501 22634 22932 23350 23313 25042 25126 23015 28838
2014 19391 22253 30969 23387 24040 25581 24700 23086 27091 25141 21855 29294
2015 19599 21643 24767 23184 22546 26852 23783 22590 25856 23159 21726 27049
2016 18970 20933 23298 19948 20837 22912 18417 20752 21299 17774 17791 19436

> plot(decompose(tsTrademarks,type="additive"))
> plot(decompose(tsPatents,type="additive"))

#Identify outliers
#Javier López-de-Lacalle (2019). tsoutliers: Detection of Outliers in Time Series. R package version 0.6-8.
# https://CRAN.R-project.org/package=tsoutliers
library(tsoutliers)
> TrademarksOutliers<-tso(tsTrademarks,types = c("AO","LS","TC"),maxit.iloop=10)
> PatentsOutliers<-tso(tsPatents,types = c("AO","LS","TC"),maxit.iloop=10)

> TrademarksOutliers
Series: tsTrademarks
Regression with ARIMA(2,1,1)(0,1,2)[12] errors
Coefficients:
    ar1  ar2  ma1  sma1  sma2 AO61  LS147  LS262
-1.0107 -0.5826  0.4306  0.4939  0.2779 12137.5320  4527.2969  3409.3950
 s.e.  0.0834  0.0440  0.1067  0.0480  0.0458  669.2913  681.1637  674.9746
sigma^2 estimated as 868751:  log likelihood=-3790.79
AIC=7599.58  AICc=7599.98  BIC=7636.74

Outliers:
    type ind    time coefhat  tstat
1   AO  61 1982:09  12138 18.135
2   LS 147 1989:11  4527  6.646
3   LS 262 1999:06  3409  5.051
Regression with ARIMA(3,0,0)(2,1,2)[12] errors

Coefficients:

|      | ar1    | ar2    | ar3    | sar1   | sar2   | sma1   | sma2   | AO61     | AO214     | AO362     | AO427     | AO362     | AO427     |
|------|--------|--------|--------|--------|--------|--------|--------|----------|-----------|-----------|-----------|-----------|-----------|
|      | 0.2731 | 0.2776 | 0.4185 | -0.3230| -1.4584| 0.6303 | 15515.5416 |          |          | 5591.8986 | 15515.5416 |          |          |
| s.e. | 0.0480 | 0.0438 | 0.0468 | 0.1133 | 0.0673 | 0.1146 | 0.0879 | 773.2661 | 764.2898  | 773.2661  | 764.2898  | 773.2661  | 764.2898  |

Outliers:

| type | ind | time  | coefhat | tstat |
|------|-----|-------|---------|-------|
| AO   | 61  | 1982:09| 5592    | 7.232 |
| AO   | 214| 1995:06| 15516   | 20.301|
| AO   | 362| 2007:10| 5058    | 6.677 |
| AO   | 427| 2013:03| 17556   | 21.950|

#Clean/smooth data - replace identified outliers (X) with average of prior (X(t-1)) and posterior (X(t+1))

```r
> plot(TrademarksOutliers); X11(); plot(PatentsOutliers)

>Trademarks<-tsTrademarks; Patents<-tsPatents
>Trademarks[61]= (Trademarks[62]+Trademarks[64]) / 2
>Trademarks[147]= (Trademarks[146]+Trademarks[148]) / 2
>Trademarks[262]= (Trademarks[261]+Trademarks[263]) / 2
>Patents[61]= (Patents[62]+Patents[64]) / 2
>Patents[214]= (Patents[213]+Patents[215]) / 2
>Patents[362]= (Patents[361]+Patents[363]) / 2
>Patents[427]= (Patents[426]+Patents[428]) / 2
```

#Lukasz Komsta and Frederick Novomestky (2015). moments: Moments, cumulants, skewness, kurtosis and related tests. R package version 0.14. https://CRAN.R-project.org/package=moments

#Use fitted output from tsoutliers

```r
>summary(Trademarks); sd(Trademarks); skewness(Trademarks); kurtosis(Trademarks)
>summary(Patents); sd(Patents); skewness(Patents); kurtosis(Patents)
```
#note: skew/kurtosis comparative - no need to transform

#Perform correlation analysis, auto- and partial-correlation and cross-wavelet
> cor(Trademarks, Patents, method="spearman");
[1] 0.9431803
> cor(Trademarks, Patents, method="kendall");
[1] 0.8024742

#Perform cross-wavelet analysis
> DATE<-seq(as.Date("1977/9/01"), as.Date("2016/12/01"), "months")
> tTrademarks <- cbind(DATE, Trademarks)
> tPatents <- cbind(DATE, Patents)
> XWTradePatent<-xwt(tTrademarks,tPatents)
Warning messages:
1: In arima(d1[, 2], order = c(1, 0, 0), method = arima.method): possible convergence problem: optim gave code = 1
2: In arima(x, order = c(1, 0, 0), method = arima.method): possible convergence problem: optim gave code = 1
> plot(XWTradePatent, xaxt="n")
> axis(side=1, at=c(seq(as.Date("1977/9/01"), as.Date("2016/12/01"), "months")),
labels=c(seq(as.Date("1977/9/01"), as.Date("2016/12/01"), "months")))

#Perform Structural Change Analysis: Confirm existence of structural break within timeseries using
#Achim Zeileis, Friedrich Leisch, Kurt Hornik and Christian Kleiber (2002). strucchange: An R Package for
#Testing for Structural Change in Linear Regression Models. Journal of Statistical Software, 7(2), 1-38.
#URL http://www.jstatsoft.org/v07/i02/

#Achim Zeileis, Christian Kleiber, Walter Kraemer and Kurt Hornik (2003). Testing and Dating o
#Structural Changes in Practice. Computational Statistics & Data Analysis, 44, 109-123.
>library(strucchange)

#Trademarks: OLS-CUSUM/OLS-MOSUM/#REC-CUSUM/REC-MOSUM
>Trademarks.olscus<- efp(Trademarks~1, type="OLS-CUSUM"); plot(Trademarks.olscus)
>Trademarks.olsmus<- efp(Trademarks~1, type="OLS-MOSUM"); plot(Trademarks.olsmus)
>Trademarks.reccus<- efp(Trademarks~1, type="Rec-CUSUM"); plot(Trademarks.reccus)
>Trademarks.recmus<- efp(Trademarks~1, type="Rec-MOSUM"); plot(Trademarks.recmus)

#Patents: OLS-CUSUM/OLS-MOSUM/#REC-CUSUM/REC-MOSUM
>Patents.olscus<- efp(Patents~1, type="OLS-CUSUM"); plot(Patents.olscus)
>Patents.olsmus<- efp(Patents~1, type="OLS-MOSUM"); plot(Patents.olsmus)
>Patents.reccus<- efp(Patents~1, type="Rec-CUSUM"); plot(Patents.reccus)
>Patents.recmus<- efp(Patents~1, type="Rec-MOSUM"); plot(Patents.recmus)

#Perform significance tests for Empirical fluctuation processes: Null hypothesis: No structural change
Short Title: Timeseries analysis of trademarks filings and patent applications: Implications on Innovation

```r
>sctest(Trademarks.olscus);sctest(Trademarks.olsmus);sctest(Trademarks.reccus);sctest(Trademarks.recmus)
>sctest(Patents.olscus);sctest(Patents.olsmus);sctest(Patents.reccus);sctest(Patents.recmus)

#Perform dating of structural change / break points via Bai-Perron

#Tradenames:
>bTrademarks<-breakpoints(Trademarks~1)
>cTrademarks<-confint(bTrademarks)

#Patents:
>bPatents<-breakpoints(Patents~1)
>cPatents<-confint(bPatents)

>cTrademarks; cPatents

>library (tseries); seqplot.ts(Trademarks,Patents); lines(cTrademarks); lines(cPatents) #R package tseries 
#(Trapletti and Hornik, 2019)

>bTrademarks; bPatents

#Based on SBPs, determine segments through heuristic of longest time between any two SBPs:
#Segment 1: 1:116    Sep 1977 to April 1987
#Segment 2: 126:186   Feb 1988 to Feb 1993
#Segment 3: 201:256   May 1994 to Dec 1998
#Segment 4: 271:329   Mar 2000 to Jan 2005
#Segment 5: 331:401   Mar 2005 to Jan 2011
#Segment 6: 403:472   Mar 2011 to Dec 2016

>tseg1<-Trademarks[1:116]; tseg2<-Trademarks[126:186]; tseg3<-Trademarks[201:256]; tseg4<-Trademarks[271:329]; tseg5<-Trademarks[331:401]; tseg6<-Trademarks[403:472]

>pseg1<-Patents[1:116]; pseg2<-Patents[126:186]; pseg3<-Patents[201:256]; pseg4<-Patents[271:329]; pseg5<-Patents[331:401]; pseg6<-Patents[403:472]

> Segment0<- as.matrix(as.data.frame(cbind(Trademarks, Patents))) #Full Dataset
> Segment1<- as.matrix(as.data.frame(cbind(Trademarks[1:116],Patents[1:116])))
> Segment2<- as.matrix(as.data.frame(cbind(Trademarks[126:186],Patents[126:186])))
> Segment3<- as.matrix(as.data.frame(cbind(Trademarks[201:256],Patents[201:256])))
> Segment4<- as.matrix(as.data.frame(cbind(Trademarks[271:329],Patents[271:329])))
> Segment5<- as.matrix(as.data.frame(cbind(Trademarks[331:401],Patents[331:401])))
> Segment6<- as.matrix(as.data.frame(cbind(Trademarks[403:472],Patents[403:472])))

#Cointegration analyses: Test for cointegration across entire and then sections
```
# Adrian Trapletti and Kurt Hornik (2019). tseries: Time Series Analysis and Computational Finance. R
# package version 0.10-47.
# Pfaff, B. (2008) Analysis of Integrated and Cointegrated Time Series with R. Second Edition. Springer,
# New York. ISBN 0-387-27960-1

> install.packages("tseries"); library(tseries)
> install.packages("urca"); library(urca)

# Johansen Procedure
> summary(ca.jo(Segment0, ecdet="const",type="trace"))
> summary(ca.jo(Segment1, ecdet="const",type="trace"))
> summary(ca.jo(Segment2, ecdet="const",type="trace"))
> summary(ca.jo(Segment3, ecdet="const",type="trace"))
> summary(ca.jo(Segment4, ecdet="const",type="trace"))
> summary(ca.jo(Segment5, ecdet="const",type="trace"))
> summary(ca.jo(Segment6, ecdet="const",type="trace"))

Philips and Ouliaris Test
> summary(ca.po(Segment0, type= "Pz"))
> summary(ca.po(Segment1, type= "Pz"))
> summary(ca.po(Segment2, type= "Pz"))
> summary(ca.po(Segment3, type= "Pz"))
> summary(ca.po(Segment4, type= "Pz"))
> summary(ca.po(Segment5, type= "Pz"))
> summary(ca.po(Segment6, type= "Pz"))

# Perform unit and stationarity assessments
> library(forecast)
> ndiffs(Trademarks, test="kpss"); ndiffs(Trademarks, test="adf"); ndiffs(Trademarks, test="pp")
> ndiffs(Patents, test="kpss"); ndiffs(Patents, test="adf"); ndiffs(Patents, test="pp")
> ndiffs(tseg1, test="kpss"); ndiffs(tseg1, test="adf"); ndiffs(tseg1, test="pp")
> ndiffs(pseg1, test="kpss"); ndiffs(pseg1, test="adf"); ndiffs(pseg1, test="pp")
> ndiffs(tseg2, test="kpss"); ndiffs(tseg2, test="adf"); ndiffs(tseg2, test="pp")
> ndiffs(pseg2, test="kpss"); ndiffs(pseg2, test="adf"); ndiffs(pseg2, test="pp")
> ndiffs(tseg3, test="kpss"); ndiffs(tseg3, test="adf"); ndiffs(tseg3, test="pp")
> ndiffs(pseg3, test="kpss"); ndiffs(pseg3, test="adf"); ndiffs(pseg3, test="pp")
> ndiffs(tseg4, test="kpss"); ndiffs(tseg4, test="adf"); ndiffs(tseg4, test="pp")
> ndiffs(pseg4, test="kpss"); ndiffs(pseg4, test="adf"); ndiffs(pseg4, test="pp")
> ndiffs(tseg5, test="kpss"); ndiffs(tseg5, test="adf"); ndiffs(tseg5, test="pp")
> ndiffs(pseg5, test="kpss"); ndiffs(pseg5, test="adf"); ndiffs(pseg5, test="pp")
```r
> ndiffs(tseg6, test="kpss"); ndiffs(tseg6, test="adf"); ndiffs(tseg6, test="pp")
> ndiffs(pseg6, test="kpss"); ndiffs(pseg6, test="adf"); ndiffs(pseg6, test="pp")
```

```
#### - End Supplementary Materials ####
```