Iberoamerican Journal of Science Measurement and Communication Vol. 1, No. 3, p. 1-23. DOI: 10.47909/ijsmc.32

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ORIGINAL ARTICLE

Leveraging latent persistency in United States patent and trademark applications to gain insight into the evolution of an innovation-driven economy

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How to cite: Daizadeh, I. (2021). Leveraging latent persistency in United States patent and trademark applications to gain insight into the evolution of an innovation-driven economy. Iberoamerican Journal of Science Measurement and Communication; 1(3), 1-23. https://doi.org/10.47909/ijsmc.32

Received: 8-12-2020

Accepted: 27-06-2021

Handling Editor: Ulf Sandströme

ABSTRACT

Objective. An understanding of when one or more external factors may influence the evolution of innovation tracking indices (such as US patent and trademark applications (PTA)) is an important aspect of examining economic progress/ regress. Using exploratory statistics, the analysis uses a novel tool to leverage the long-range dependency (LRD) intrinsic to PTA to resolve when such factor(s) may have caused significant disruptions in the evolution of the indices, and thus give insight into substantive economic growth dynamics.

Design/Methodology/Approach. This paper explores the use of the Chronological Hurst Exponent (CHE) to explore the LRD using overlapping time windows to quantify long-memory dynamics in the monthly PTA time series spanning 1977 to 2016.

Results/Discussion. The CHE is found to increase in a clear S-curve pattern, achieving persistence (H~1) from non-persistence (H~0.5). For patents, the inflection occurred over a span of 10 years (1980-1990), while it was much sharper (3 years) for trademarks (1977-1980).

Conclusions/Originality/Value. This analysis suggests (in part) that the rapid augmentation in R&D expenditure and the introduction of the various patent-directed policy acts (e.g., Bayh-Dole, Stevenson-Wydler) are the key factors behind persistency, latent in PTA. The post-1990's exogenic factors seem to be simply maintaining the high degree and consistency of the persistency metric. These findings suggest investigators should consider latent persistency when using these data and the CHE may be an important tool to investigate the impact of substantive exogenous variables on growth dynamics.

Keywords: Innovation, Hurst, trademarks, patents, persistency, economy

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INTRODUCTION

Intellectual property (IP)-based metrics (initially patents and more recently trademarks) have been used as proxy measures of global politico-socio-economic innovative behavior [on the micro (firm)-, meso (research institution, cluster)-, and/or macro (country/regional)-level] for decades (see, e.g., Dziallas and Blind, 2019). These and related indices focus on the time-dependent ebbs and flows of absolute counts of observations and/or derivates thereof. Importantly, it is understood that these data integrate one or more extrinsic forces and/or factors that are either directly or indirectly influenced the chronological evolution of these data in some way (see, e.g., Daizadeh, 2007, 2009, 2021). Indeed, a vast majority of this research either test or generate a hypothesis of how such extrinsic impulses – such as the promulgation of a specific policy framework, gross effects of research and development expenditures, sector-specific technology dynamics (e.g., disruptive versus incremental) – may affect the time course of these IP-metrics (see, e.g., Grimaldi and Cricelli, 2020; Flikkema, et al., 2015; Daizadeh, 2007, 2021). Unfortunately, to the author's knowledge, there are limited-to-no inquiries exploring the intrinsic make-up of these time-series data.

Even in the simplest of cases, the interpretative potential of time series data, such as those of patents and trademarks, may be challenging, however, due to their intrinsic behavior (s) (see, e.g., Cheng et al., 2015). Importantly and simultaneously, some of these properties are also of interest due to the potential to elucidate interesting dynamics. For example, memory characteristics across length scales (short, medium, and long) suggest the existence of various economic cycles (see, e.g., Alvarez-Ramirez et al., 2020). Concordantly, these same memory characteristics can obfuscate true signal detection, due to – for example – mistakenly considering long-memory and non-stationary complex dynamics (see, e.g., Saha et al., 2020). Other properties such as linearity, normality, and seasonality of the time series may further exacerbate misinterpretations. Statistical time series practitioners exert great effort in developing methods that would increase the certitude of the interpretation by accommodating one or more of these properties. Resolving the suite of issues is the first step in establishing robust statistical approaches and increased confidence in model interpretability.

The Hurst exponent is a statistical time-series tool that has been used to better understand memory effects in time series data and has been applied to various fields including earth sciences (see, e.g., Slino, et al., 2020), economics (see, e.g., Wu and Chen, 2020), and others. While there are other ways, the Hurst exponent (a measurement of memory) is classically defined as $H \sim \ln(R / S)_t / \ln(t)$, where R and S are the rescaled range and standard deviation, respectively, and t is a time window. An $H=0.5$, an $H<0.5$, and an $H>0.5$ indicate a random walk (non-persistent), an anti-persistent, and a persistent (trend reinforcing) time series behavior, respectively (see, e.g., Mandelbrot and Wallis, 1968, 1969).

To the author's knowledge, there have not been any investigations of the Hurst exponent with regards to either patents or trademarks. In terms of patents, however, some elements of memory effects have been explored in the context of economic cycles by several authors (see, e.g., Korotayev, 2011; Haustein and Neuwirth, 1982, Alvarez-Ramirez, 2020, Epicoco, 2020, Daizadeh, 2021a). Korotayev et al (2011) demonstrated a Kondratieff (K)-wave pattern when investigating the dynamics of the annual number of global patents per million population from 1900 to 2008. As summarized by (Alvarez-Ramirez, 2020), Korotayev showed that patents presented with "a steady increase during the upswing phase of Kondratieff's cycle, and a pronounced decrease during the downswing phase." Haustein and Neuwirth (1982) found that "industrial production on patents with a lag of 9 years." More recently, Epicoco (2020) fitted the information and communications technologies cycle with that of the economy using patent and productivity data and proposed "the current productivity slowdown may be a signal that the economic system needs to change its leading technologies."

Carbone, Castelli, and Stanley (2004) proposed a time-dependent Hurst exponent based on a detrending moving average (DMA). Here, the Hurst exponent is a log-log slope of the DMA standard deviation against window (see equations 1 and 2 therein). The authors conclude from an analysis of artificial and observed time series of financial data that the time-variability is much "richer" than anticipated from a mono-fractal approach. To accommodate non-stationary effects, the work was subsequently extended with the aid of detrended fluctuation analysis over non-overlapping window lengths by Alverez-Ramirez and colleagues (2020). Effectively, these approaches to time-dependent Hurst exponent calculations are model parameterized.

In this work, and as described in the Methodology section below, a non-model parameterized chronological Hurst exponent (CHE) is proposed that when applied to a given time series may identify significant changes in the persistency of memory. The method is straightforward to implement since it simply uses a standard estimate of the Hurst exponent calculated from the initial time point to month a, where a is a monthly increment. The output of the CHE calculation is described as the time series plot of each of the Hurst exponents, allowing a qualitative view of the Hurst exponent over a given time period (see Methods). This approach allows for an arbitrary method to calculate the Hurst exponent while taking into regard the nuances of the time series. Here, the method is applied to US patent and trademark applications (PTA) from 1977-2016. The date range selected is chronologically broad (a period of over 40 years) and used in prior work, and thus presented here. Interested readers may extend the data range accordingly, as all data and R Programs used for this manuscript are available (Appendix; Daizadeh, 2021b).

As described in the Results section below, from the application of this novel tool to PTA, it is found that the CHE evolves in a highly descriptive and idiosyncratic S-like pattern: from non-persistent (H~0.5) to saturation (trend reinforcing persistent (H~1) level via a quickly evolving inflection period (see Figures 1-3). For patents, the inflection occurred over a span of 10 years (1980-1990), while it was much sharper (3 years) for trademarks (1977-1980). As will be further discussed below, these findings suggest: investigators should consider latent persistency when using these data; exogenous factors after the identified inflection points for these indices have only incrementally strengthened intrinsic memory; and, the CHE may be an important tool to investigate the impact of substantive exogenous variables on growth dynamics. Qualitative correlation of the timing of the inflection points for patents and trademarks suggests the importance of research and development expenditure.

METHODOLOGY

The data were comprised of the monthly number of US patent applications (Patents) and the monthly number of US trademarks filings (Trademarks) (together, PTA) from 1977 to 2016, and were obtained from the United States Patent and Trademark Office (USPTO) as described below:

- Patents:
  - Website: http://patft.uspto.gov/netahtml/PTO/search-adv.htm
  - Search pattern: Application Filing Date: "APD/MM/$/YYYY"
- Trademarks:
  - Website: http://tmsearch.uspto.gov/bin/gate.exe?f=tess&state=4804:57thz4.1.1
  - Search pattern: Filing Date: "(YYYYMM$)[FD]"

Note: MM/YYYY is the 2/4 digital representation for month/year. The two searches resulted in 472 datapoints – representing monthly observations over the period of study (approximately 40 years) – for each variable and imported into R for processing (Appendix; Daizadeh, 2021b).

The methodology followed standard implementation, and default parameters were used throughout. The general algorithm for the analysis is as follows:

- Load time series (R package 'tseries' (Trapletti and Hornik, 2019)), identify and replace outliers with an 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).
- Calculate descriptive statistics [including standard deviation, kurtosis, and skew (R package 'moments' (Komsta and Novomestky, 2015)] and auto/serial correlation (base R package).
- Calculate intrinsic variables: normality (R package 'nortest' (Gross and Ligges, 2015)), stationarity (R package 'forecast' (Hyndman, et al., 2020; Hyndman and Khandakar, 2008; R package 'aTSA' (Qiu, 2015)), seasonality (R package 'seastests' (Ollech, 2019)), and non-linearity (R package 'nonlinearTseries' (Garcia, 2020))
- Calculate chronological Hurst exponent: Determine Hurst exponent based on Hyndman implementation (R package 'tsfeatures' (Hyndman et al, 2020)) using the following algorithm:
-
    - for (i in start:end) { hurst-IP[i] <- hurst (time[1:(1+i*1)]) }, where IP is either Trademarks or Patents; start = September, 1977; end = December 2016; I = monthly increments
    - Note: The Hyndman approach – one of several methods to calculate (estimate) the Hurst Exponent (Shang, 2020) – is defined as 0.5 plus the maximum likelihood estimation of the fractional differencing order (see Hyndman et al, 2020); thus, it has properties that differ than Hurst's original definition (e.g., no singularities at certain scales). In principle, any approach should produce qualitatively the same result as that outline above, albeit additional work is required to confirm the approaches sensitively.

RESULTS AND DISCUSSION

General Statistics

Generally, the time series were similar in structure with a general cobra-like structure (see upper graphs of Figures 1, 2, and 3) and similarities in the shape of the distributions (e.g., approximately symmetric (skew) and platykurtic) (see Table 1). The time series showed clear long-memory tendency as presented in the auto and serial correlation functions with lag much great than 2. Lastly, both time series were non-normal, non-stationary [with a single difference ((t-1) – t) bringing them into stationarity – that is, integration of order 1 typical of econometric data], seasonal, and non-linear (see Table 2).

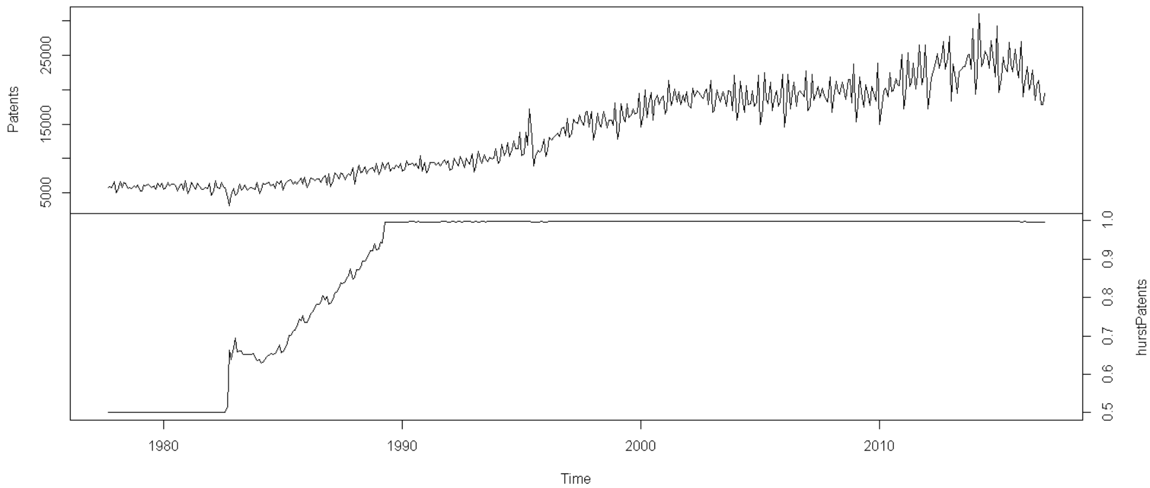

Figure 1. The monthly number of Patents (top graph) from 1977-2016 with its corresponding chronological Hurst values (bottom graph).

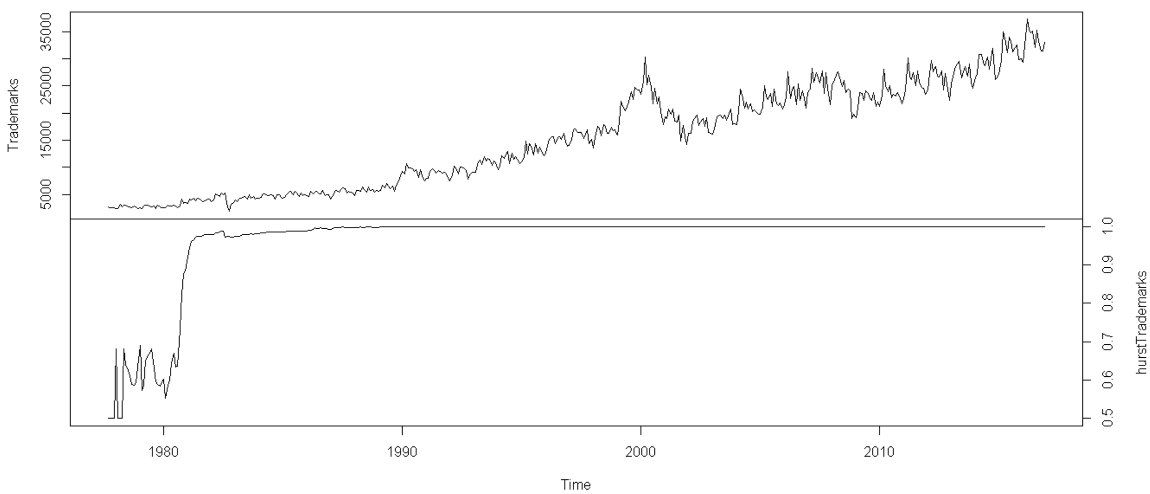

Figure 2. The monthly number of Trademarks (top graph) from 1977-2016 with its corresponding chronological Hurst values (bottom graph).

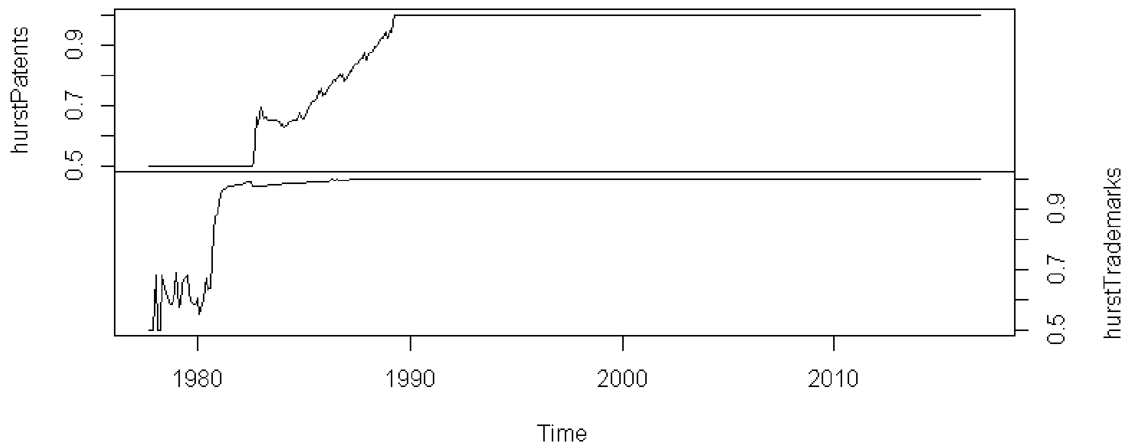

Figure 3. Comparison of chronological Hurst values between Patents and Trademarks.

Table 1. Descriptive statistics of Patents and Trademarks.

	Patents	Trademarks
Minimum	3134	1895
1st Quantile	7598	5537
Median	14468	15456
Mean	13930	15276
3rd Quantile	19422	23574
Maximum	30969	37317
Stand Deviation	6523.347	9418.054
Skewness	0.1854975	0.2020644
Kurtosis	1.757654	1.763723

Table 2. General results of intrinsic parameters of Patents and Trademarks (see Appendix; Daizadeh, 2021b).

	Patents	Trademarks
Normality	Non-normal	Non-normal

	Patents	Trademarks
Stationarity	Non-stationary (order of integration: 1)	Non-stationary (order of integration: 1)
Seasonality	Seasonal	Seasonal
Non-linearity	Non-linear	Non-linear

Chronological Hurst Exponent

Examining Figures 1 and 2, the time evolution of PTA shows a general trend-reinforcing pattern, edging generally up with time. There are variations of course partly due to the identified seasonal effects. The Chronological Hurst Exponent (CHE) correspondingly evolves, with non-persistence (H~0.5) near the beginning of the time series (notice: this is where the absolute counts of the PTA are effectively static). As the time series evolves, the CHE quickly jumps to saturation (H~1). A Hurst exponent at such a high relative value suggests that that the trend will continue to persist in the original time series – that is, the exponent reflects the similarity of prior absolute values of PTA to future values; in other words: as prior timepoints values edge up, it is likely that the next value will also be up. This is consistent with the long auto and serial correlations in the original time series.

Co-positioning PTA CHE (as in Figure 3), a similarity in S-structure is presented. The scaling regimes of are trichotomized in both time series into the following periods: (1) non-persistence (albeit for Trademarks mild persistence is observed with H values oscillating between 0.5 and 0.7); (2) time-varying persistence (an inflection, where H slopes from 0.5/0.6 to near 1); and, (3) persistence (H~1). Specifically, it is found that:

- Period 1: Weak to no persistence prior to 1980s:
-
  - Patents: The flat H exponent, as shown in Figure 1 (lower graph) and Figure 3 (upper graph), reflects the neutral acceleration in the time series.
  - Trademarks: The variation in H exponent (~0.5 to ~0.7) reflects a positive trajectory as depicted in Figures 2 (upper graph) and 3 in the reference time series.
- Period 2: A time-varying Hurst exponent up to and during the 1980s and 1990s
  - Patents: The value of the H exponent began to grow with a rapid linear rate of approximately 0.1-0.2 Hurst values per year, commencing with an explosive charge in the mid-1980s, and terminating with saturation before 1990.
  - Trademarks: The value of the H exponent grew at an exceptional rate at roughly 0.3 over two years, from effective baseline to near saturation by 1983.
- Period 3: Saturated persistence for trademarks beginning by 1983 and for patents in the 1990s throughout the duration of the reporting period 2016.

Focusing on the time-varying Period 2, while more work needs to be done to better our understanding of the dynamics in the 1980s and 1990s that affected these proxy measures of innovativeness, some thoughts present themselves for potentially testable causality hypotheses:

- Economic: Total spending on research and development grew from $60B USD in 1975 to $100B by 1985, concomitantly while the contribution from industry to the percent of Gross Domestic Product rose from 1% to nearly 1.5% during that same time (see Figure 1 in Hunt, 1999). Indeed, patent activity (number of Patent Applications) also doubled grew from 100k

(1980) to 200k (2000) (see Figure 2 in *ibid*). Could industrial R&D expenditures directly drive the persistence of Patents and Trademarks?

- Policy: There were significant competitive policy initiatives during the 1980s including the Bayh-Dole Act (Patent and Trademark Law Amendments Act (Pub. L. 96-517, December 12, 1980), Public Law 96-480, Stevenson-Wydler Technology Innovation Act (as amended in 1986 and 1990), and others (see Table 1 in Coriat and Orsi, 2002). Was the persistency initiated by one or more of these policies (including, for example, new patentability types: software and/or business plans)?
- Technology dynamics: S-shaped growth for individual technological innovations may contribute to the overall Patent evolution dynamic (see, e.g., Anderson, 1999). A linear combination of such patent growths may be affecting the persistence of the overall Patents structure. To the author's knowledge, there is limited to no information on any S-shaped distribution for Trademarks, the potential for future queries. Do technology dynamics associated with innovation cumulatively affect persistence in the innovation metrics?

CONCLUSION

The goal for the use of a novel method – termed the chronological Hurst exponent (CHE) – to investigate long-term memory dynamics in time series data is to describe the overall persistency tend and, importantly, to identify the key dates in which there is a change in persistency (anti-persistence, non-persistence, persistence). Here, the CHE was applied to two innovative-tracking, intellectual property-driven data: the monthly numbers of patent and trademark applications. CHE is a simple to use method, trivially constructed in any programming language (Appendix; Daizadeh, 2021b) and easily applied to longitudinal data. Additional work is required to better understand the approach, including using different memory quantification tools (e.g., different versions of the Hurst exponent calculation) and different (longer) datasets with different characteristics.

In summary, this paper presents the first use of the CHE as well as the initial results of its application to PTA. The importance of persistency as an intrinsic factor of time series data should not be underestimated as effects such as trend-reinforcing behavior may lead to biased results when interpreting time-series data, as the momentum of the time series may cover salient investigative concerns (recall that the Hurst exponent is a measure of self-similarity). It is a hope of this work that investigators continue to examine the innovative accomplishments of the late 20th century as well as consider persistency measures in current assessments of techno-economic progress.

Conflict of Interest Statement

The author is an employee of Takeda Pharmaceuticals; however, this work was completed independently of his employment. The views expressed in this article may not represent those of Takeda Pharmaceuticals.

Statement of Data Consent

The data generated during the development of this study has been included in the manuscript.

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APPENDIX: R CODE FOR TRANSPARENCY AND REPRODUCIBILITY

Start: R code with dataset

#Trademarks
#Go to TESS: 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
#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:

```
> 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/.

```
> version
_
platform x86_64-w64-mingw32
arch x86_64
os mingw32
system x86_64, mingw32
status
major          3
minor          6.1
year           2019
month          07
day            05
svn rev        76782
```

language   R
version.string R version 3.6.1 (2019-07-05)
nickname   Action of the Toes

#Read into R:

> IP<- read.csv("…/data.csv", sep=",")

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

> str(IP)

'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 6630 5064 5439 6660 5799 6487 6419 ...

Shrinking by 24 months dues 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	2362
1979	2518	2350	2920	2968	2953	2794	2741	2829	2438	2956	2676	2596
1980	2469	2607	3035	2893	2797	3094	2883	2590	2928	4081	3412	3559
1981	3329	4113	3906	4297	3871	4358	4077	3815	3688	3879	4162	4140
1982	3594	4009	5128	4868	4576	5244	4942	5264	15843	1895	3126	3529
1983	3915	3597	4224	4297	4389	4543	4192	4893	4265	4634	4189	4296
1984	4281	4472	5167	5068	4762	4837	4914	4803	4064	4896	4922	4474
1985	4296	4408	5087	5417	5537	4914	5537	5215	4627	5218	4747	4904
1986	4785	4677	5569	5153	5397	5630	5152	5124	5715	4787	4950	4931
1987	4188	4826	5528	5780	5372	5860	6269	5990	5309	5624	5454	5286
1988	4758	5756	5730	5618	6358	5706	5473	6341	5776	5899	5384	5744
1989	5546	5761	6615	6230	7071	6496	5995	6567	5613	6687	11400	8450
1990	9209	8797	10687	9936	9836	9707	9319	9634	8167	9567	8417	7546
1991	7906	7986	9192	9734	9441	8962	9371	9260	8884	9073	8805	7972
1992	7486	8612	10248	9940	8776	10078	10019	9701	9348	7853	8599	9107
1993	9143	9143	11059	11352	10594	11897	11160	11628	11448	10374	11248	10923
1994	9599	10388	12173	11664	12292	12902	10728	12536	11443	11932	11339	10634
1995	10961	11857	14860	12391	14323	13644	12325	14434	12631	13726	12926	12072
1996	12582	13872	15117	15636	15565	14433	15447	15590	15234	16299	14727	13810

```
1997 14060 15229 16962 17079 16460 16465 16425 15363 16089 16901 14367 15163
1998 13510 15465 17624 17224 15805 17862 17515 16270 16331 17426 16737 16897
1999 16002 18431 22143 20957 20515 24106 21999 23891 22563 24753 24225 24272
2000 23412 25815 30423 25204 26986 24831 21769 24626 21644 22962 20340 17822
2001 19248 18923 20732 19781 20778 18551 18311 19608 14770 17727 15587 14181
2002 16273 16357 18555 18946 19622 17734 18359 18958 17639 19111 16487 16278
2003 16170 17077 19352 19461 19563 19045 19687 18614 19518 20752 17857 18083
2004 17848 20221 24380 22857 20851 21971 20794 21686 20329 20545 20163 19727
2005 19852 21156 25021 23106 22583 23621 21283 24405 21769 21419 21833 20716
2006 21532 22810 27578 22750 24386 24861 21580 25319 22311 24077 22658 20909
2007 23774 24365 28236 25640 27467 26565 25520 27860 23629 27407 24521 21614
2008 25011 25689 27048 27577 26586 24960 26086 23857 24425 24124 19074 19873
2009 19111 20849 23869 23573 22337 24084 23578 22625 22336 23795 21248 21987
2010 21221 23097 28105 25119 23953 25080 22796 23413 23092 23739 23151 21794
2011 22686 24232 30145 26896 26187 27407 25024 27708 25636 24807 24550 23480
2012 24295 27305 29660 27660 28521 26754 26636 27794 24270 27369 24447 22310
2013 25382 26630 28633 29002 29609 26566 27697 28612 26811 28991 25622 24625
2014 26543 27243 30853 30752 29450 28680 30393 28186 30059 32019 26212 26558
2015 27182 29681 35025 33786 31123 34043 33316 31327 32138 32584 29909 30094
2016 29461 32456 37317 35506 34861 35211 32027 35356 33293 31394 31452 33063
```

```
> tsPatents
       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  5692
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 21285 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
```

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2005 14968 17021 22490 18546 17987 21090 16914 18462 19787 17592 18133 22188
2006 14550 16701 22216 17208 19402 21150 17560 19571 19828 19312 18999 22766
2007 16930 17539 22271 18427 19480 20506 18797 20267 19143 25045 18195 21820
2008 16717 18825 21168 19762 19318 21035 19896 18546 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

> PatentsOutliers
Series: tsPatents
Regression with ARIMA(3,0,0)(2,1,2)[12] errors
Coefficients:
       ar1     ar2     ar3    sar1     sar2     sma1     sma2       AO61       AO214
    0.2731  0.2776  0.4185  0.7318  -0.3230  -1.4584  0.6303  5591.8986  15515.5416
s.e.  0.0480  0.0438  0.0468  0.1133   0.0673   0.1146  0.0879   773.2661    764.2898
        AO362       AO427
    5058.3040  17555.5353
s.e.   757.5541    799.8064
sigma^2 estimated as 917822:  log likelihood=-3812.79
AIC=7649.58   AICc=7650.27   BIC=7699.15
```

```
Outliers:
 type ind    time coefhat  tstat
1   AO  61 1982:09    5592  7.232
2   AO 214 1995:06   15516 20.301
3   AO 362 2007:10    5058  6.677
4   AO 427 2013:03   17556 21.950

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

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

>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

> plot(decompose(Trademarks,type="additive"))
> plot(decompose(Patents,type="additive"))

> library(moments); citation("moments")

#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

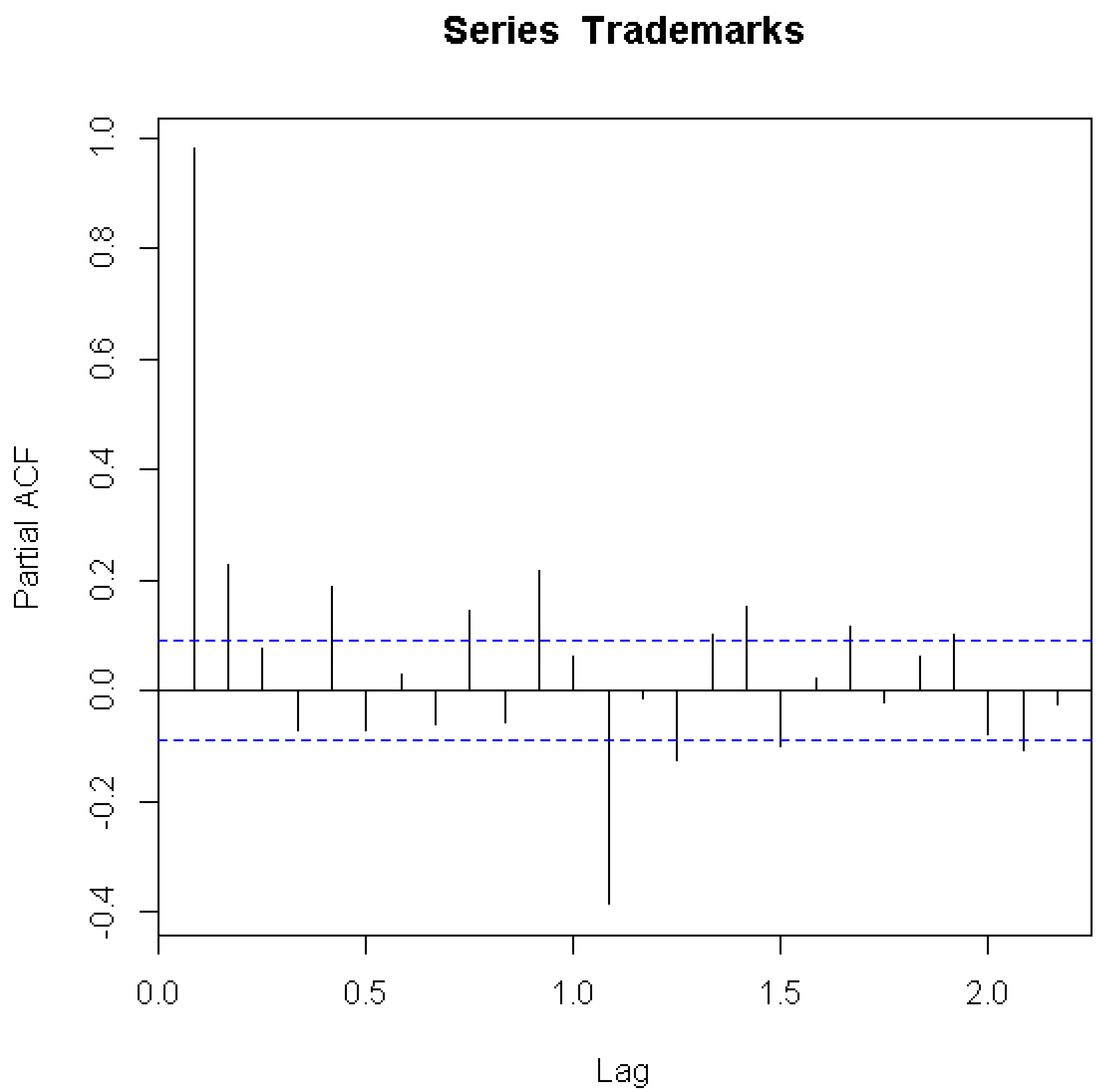
#Use fitted output from tsoutliers

>summary(Trademarks); sd(Trademarks); skewness(Trademarks); kurtosis(Trademarks)
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1895    5537   15456   15276   23574   37317
[1] 9418.054
[1] 0.2020644
[1] 1.763723
>summary(Patents); sd(Patents); skewness(Patents); kurtosis(Patents)
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
3134    7598   14468   13930   19422   30969
[1] 6523.347
[1] 0.1854975
[1] 1.757654

#note: skew/kurtosis comparative - no need to transform

#auto/serial correlation

acf(Trademarks);pacf(Trademarks)
```



acf(Patents);pacf(Patents)

#Perform normality, stationarity, seasonality, long-memory, and non-linearity tests
> #normality test

> library(nortest);citation("nortest")

To cite package ‘nortest’ in publications use: Juergen Gross and Uwe Ligges (2015). nortest: Tests for Normality. R package version 1.0-4.   https://CRAN.R-project.org/package=nortest

> ad.test(Trademarks) #null normality

        Anderson-Darling normality test
data: Trademarks
A = 11.055, p-value < 2.2e-16

> ad.test(Patents) #null normality

Anderson-Darling normality test
data: Patents
A = 13.102, p-value < 2.2e-16

> cvm.test(Trademarks)

Cramer-von Mises normality test
data: Trademarks
W = 1.7112, p-value = 7.37e-10

Warning message:
In cvm.test(Trademarks) : p-value is smaller than 7.37e-10, cannot be computed more accurately

> cvm.test(Patents)

Cramer-von Mises normality test
data: Patents
W = 2.2197, p-value = 7.37e-10

Warning message: In cvm.test(Patents) : p-value is smaller than 7.37e-10, cannot be computed more accurately

> #stationary test

>library(forecast)
>ndiffs(Trademarks, test= "kpss"); ndiffs(Trademarks, test= "adf"); ndiffs(Trademarks, test= "pp")
[1] 1
[1] 1
[1] 1
>ndiffs(Patents, test= "kpss"); ndiffs(Patents, test= "adf"); ndiffs(Patents, test= "pp")
[1] 1
[1] 1
[1] 1

> library(aTSA)

Attaching package: ‘aTSA’
The following object is masked from ‘package:forecast’:forecast
The following object is masked from ‘package:graphics’: identify

> citation("aTSA")
To cite package ‘aTSA’ in publications use: Debin Qiu (2015). aTSA: Alternative Time Series Analysis. R package version 3.1.2. https://CRAN.R-project.org/package=aTSA

> stationary.test(Trademarks, method="kpss")

KPSS Unit Root Test alternative: nonstationary

Type 1: no drift no trend
lag stat p.value

```
5 0.59     0.1
-----

Type 2: with drift no trend
lag  stat p.value
5 0.751    0.01
-----

Type 1: with drift and trend
lag  stat p.value
5 0.181   0.023
-----------
Note: p.value = 0.01 means p.value <= 0.01: p.value = 0.10 means p.value >= 0.10

> stationary.test(Patents, method="kpss")

KPSS Unit Root Test alternative: nonstationary

Type 1: no drift no trend
lag stat p.value
5 5.88    0.01
-----
Type 2: with drift no trend
lag stat p.value
5 5.53    0.01
-----
Type 1: with drift and trend
lag  stat p.value
5 0.524    0.01
-----------
Note: p.value = 0.01 means p.value <= 0.01: p.value = 0.10 means p.value >= 0.10

#Now the first diffs

stationary.test(diff(Trademarks), method="kpss")

KPSS Unit Root Test alternative: nonstationary

 Type 1: no drift no trend
lag  stat p.value
5 0.642     0.1
-----
Type 2: with drift no trend
lag   stat p.value
5 0.0294     0.1
-----
Type 1: with drift and trend
lag  stat p.value
5 0.015     0.1
-----------

Note: p.value = 0.01 means p.value <= 0.01: p.value = 0.10 means p.value >= 0.10
```

```
stationary.test(diff(Patents), method="kpss")
KPSS Unit Root Test
alternative: nonstationary
Type 1: no drift no trend
lag  stat p.value
5 0.799     0.1
-----
Type 2: with drift no trend
lag   stat p.value
5 0.0858     0.1
-----
Type 1: with drift and trend
lag   stat p.value
5 0.0716     0.1
-----------
Note: p.value = 0.01 means p.value <= 0.01 : p.value = 0.10 means p.value >= 0.10
```

#Long memory

```
> library(LongMemoryTS); citation("LongMemoryTS")
```

To cite package ‘LongMemoryTS’ in publications use: Christian Leschinski (2019). LongMemoryTS: Long Memory Time Series. R package version 0.1.0. https://CRAN.R-project.org/package=LongMemoryTS

#Qu Test

```
> Qu.test(diff(Trademarks),m)
$W.stat [1] 1.432811

$CriticalValues

eps=.02 eps=.05
alpha=.1     1.118   1.022
alpha=.05    1.252   1.155
alpha=.025   1.374   1.277
alpha=.01    1.517   1.426

> Qu.test(diff(Patents),m)
$W.stat [1] 2.334971

$CriticalValues

          eps=.02 eps=.05
alpha=.1     1.118   1.022
alpha=.05    1.252   1.155
alpha=.025   1.374   1.277
alpha=.01    1.517   1.426

> #multivariate local Whittle Score

> MLWS(diff(Trademarks), m=m)

$B
```

```
     [,1]
[1,]    1

$d [1] -0.3782234

$W.stat [1] 1.502709

$CriticalValues

  alpha=.1  alpha=.05 alpha=.025  alpha=.01
1.118      1.252      1.374      1.517

> MLWS(diff(Patents), m=m)

$B
     [,1]
[1,]    1

$d [1] -0.3440901

$W.stat [1] 2.43958

$CriticalValues

  alpha=.1  alpha=.05 alpha=.025  alpha=.01
1.118      1.252      1.374      1.517

> #seasonality tests

> library(seastests); citation("seastests")
```

To cite package ‘seastests’ in publications use: Daniel Ollech (2019). seastests: Seasonality Tests. R package version 0.14.2. https://CRAN.R-project.org/package=seastests

```
> summary(wo(Trademarks))

Test used:  WO
Test statistic:  1
P-value:  0 0 0

The WO - test identifies seasonality

> summary(wo(Patents))

Test used:  WO
Test statistic:  1
P-value:  0 0 0

The WO - test identifies seasonality

> isSeasonal(Trademarks,"qs"); isSeasonal(Trademarks,"fried"); isSeasonal(Trademarks,"welch");
```

[1] TRUE
[1] TRUE
[1] TRUE

> isSeasonal(Patents,"qs"); isSeasonal(Patents,"fried"); isSeasonal(Patents,"welch");

[1] TRUE
[1] TRUE
[1] TRUE

#Nonlinearity Tests

> library(nonlinearTseries); citation("nonlinearTseries")

Attaching package: ‘nonlinearTseries’ The following object is masked from ‘package:aTSA’: estimate

The following object is masked from ‘package:grDevices’: contourLines

To cite package ‘nonlinearTseries’ in publications use: Constantino A. Garcia (2020). nonlinearTseries: Nonlinear Time Series Analysis. R package version 0.2.10. https://CRAN.R-project.org/package=nonlinearTseries

> nonlinearityTest(Trademarks)

** Teraesvirta's neural network test **
Null hypothesis: Linearity in "mean"
X-squared = 13.65589 df = 2 p-value = 0.001083081

** White neural network test **
Null hypothesis: Linearity in "mean"
X-squared = 14.43927 df = 2 p-value = 0.00073207

** Keenan's one-degree test for nonlinearity **
Null hypothesis: The time series follows some AR process
F-stat = 0.04386686 p-value = 0.8342031

** McLeod-Li test **
Null hypothesis: The time series follows some ARIMA process
Maximum p-value = 0

** Tsay's Test for nonlinearity **
Null hypothesis: The time series follows some AR process
F-stat = 3.041166 p-value = 8.100652e-10

** Likelihood ratio test for threshold nonlinearity **
Null hypothesis: The time series follows some AR process
Alternativce hypothesis: The time series follows some TAR process
X-squared = 51.55873 p-value = 0.03278644

> nonlinearityTest(Patents)

** Teraesvirta's neural network test **

Null hypothesis: Linearity in "mean"
X-squared = 110.8611 df = 2 p-value = 0

** White neural network test **
Null hypothesis: Linearity in "mean"
X-squared = 108.337 df = 2 p-value = 0

** Keenan's one-degree test for nonlinearity **
Null hypothesis: The time series follows some AR process
F-stat = 3.379455 p-value = 0.06672325

** McLeod-Li test **
Null hypothesis: The time series follows some ARIMA process
Maximum p-value = 0

** Tsay's Test for nonlinearity **
Null hypothesis: The time series follows some AR process
F-stat = 6.296795 p-value = 1.162674e-15

** Likelihood ratio test for threshold nonlinearity **
Null hypothesis: The time series follows some AR process
Alternative hypothesis: The time series follows some TAR process
X-squared = 78.45917 p-value = 2.60603e-05

```
> library(tsfeatures); citation("tsfeatures")
```

To cite package ‘tsfeatures’ in publications use: Rob Hyndman, Yanfei Kang, Pablo Montero-Manso, Thiyanga Talagala, Earo Wang, Yangzhuoran Yang and Mitchell O'Hara-Wild (2020). tsfeatures: Time Series Feature Extraction. R package version 1.0.2. https://CRAN.R-project.org/package=tsfeatures

```
hurstTrademarks=0;hurstPatents=0

endT<-length(Trademarks); endP<-length(Patents)

for (i in 1:endT) { hurstTrademarks[i] <- hurst (Trademarks[1:(1+i*1)]) }

for (i in 1:endP) { hurstPatents[i] <- hurst (Patents[1:(1+i*1)]) }

hurstTrademarks<-ts(hurstTrademarks,start=c(1977,9),end=c(2016,12), frequency=12)

hurstPatents<-ts(hurstPatents,start=c(1977,9),end=c(2016,12), frequency=12)
plot(hurstTrademarks); plot(hurstPatents)

> library(tseries);citation("tseries")
```

‘tseries’ version: 0.10-47 ‘tseries’ is a package for time series analysis and computational finance. See ‘library(help="tseries")’ for details.

Attaching package: ‘tseries’ The following objects are masked from ‘package:aTSA’: adf.test, kpss.test, pp.test

To cite in publications use:

Adrian Trapletti and Kurt Hornik (2019). tseries: Time Series Analysis and Computational Finance. R package version 0.10-47.

plot(ts.intersect(Patents, hurstPatents),main="", yax.flip=TRUE)

plot(ts.intersect(Trademarks, hurstTrademarks),main="", yax.flip=TRUE)

plot(ts.intersect(hurstPatents, hurstTrademarks),main="", yax.flip=TRUE)

End