An Analysis of Macroeconomic Fluctuations on the Number of Patents Awarded in the United States

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Abstract

We examine the extent to which U.S. patent applications and patents granted respond to the cyclical variation of the U.S. economy as reflected by major macroeconomic aggregates such as real GDP and others. We find that patents granted are cointegrated with GDP and research and development indicating a long run stochastic relationship among these variables. We also find Granger Causality going from the growth in real GDP to the number of patents granted. In particular, our findings show that past changes in the growth rate of real GDP leads to increases in the future rate of growth of patents granted. As expected, R&D is also related patents granted to although its relationship with patents granted is weaker than with real GDP.

I. Introduction

U. S. companies invest significant sums in research and development to create new products to sell in the marketplace. Patent rights have been created to try to allow the developers of specific intellectual property to enjoy the exclusive ability to market that product for a limited period of time. In the United States, these protections are provided for by Title 35 of the United States Code. Title 35 stipulates that the patentee has the exclusive right to manufacture, use and market an invention in the United States. Patents are obtainable on products and processes as well as computer algorithms. However, one cannot patent an idea.

In the United States, patents are awarded by the U.S. Patent and Trademark Office (USPTO). In 2010, 219,614 utility patents were granted by the USPTO. There were 490,226 applications of which 45% were granted. The awarding of a patent is the outcome of a process where the applicant provides the patent office with a written description of the invention and sets forth various claims that define the property right the applicant is seeking. As part of this process the applicant has a duty to describe any prior art and previous patents that are relevant to the patentability of the invention in question. The patent office may grant the patent or reject the application after which the applicant has the right to appeal or file a notice of abandonment. It is common for the USPTO's patent examiners to initially reject a patent application and indicate perceived problems with the claims in the application which the applicant must address. The "back and forth" of this process can involve 3-4 years.[1] The length of this time period is deceiving as examiners may devote on average less than twenty hours on the review over this entire time period. This is part of the reason why the ex-ante review process is generally regarded as "light."[2]

The USPTO issues several different types of patents. They include utility, design, plant, reissue patents. Approximately 90% of the patents that are issued are utility patents. These are patents which are issued for new processes or machines.

U. S. patent owners must pay an annual fee to renew and maintain a patent they have been awarded. This fee increases with the age of the patent. Therefore, patent

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[1] J. R. Allison and Mark A. Lamley, "Who's Patenting What? An Empirical Exploration of Patent Prosecution," *Vanderbilt law Review*, 53, 2000, 2099-2174.

[2] Mark A. Lamley, "Rational Ignorance at the Patent Office," *Northwestern University Law Review*, 95, 2001, 1495-1532.

holders have to annually evaluate the current value of the return from holding the patent compared to the costs of renewal.[3]

Patent lawsuits are filed in federal court. In 1982 a centralized appellate court system, the Court of Appeals for the Federal Circuit, was established with the goal of making patent protection more consistent and enhancing the rights of patent owners. Specifically, the "new" court supported broader exclusionary rights of patent owners through an expanded interpretation of patent scope while also making evidentiary challenges to patents more difficult to implement.[4] Courts have considerable discretion in determining the relevant scope of a patent.[5]

Since the establishment of the Court of Appeals, the success rates of plaintiffs in patent actions increased and this, in turn, seem to have increased the number of patent lawsuits.[6] The period after the establishment of this court also coincided with an upswing in the number of U.S. patents leading some to suspect that it was an important causal factor. However, Kortum and Lerner failed to find support for this conclusion.[7] Firstly, they showed that the numbers of patents were already increasing prior to 1982. In addition, they tested this hypothesis by seeing if the establishment of the court made the U.S. a more important court for international patent filers – the so-called friendly court hypothesis. They failed to find support for this hypothesis. Thus they concluded that the establishment of the court was not an important explanatory factor.

Jaffe and Lerner contend that the combination of the establishment of the specialized patent Court of Appeals, as well as other changes that occurred at the Patent Office in the early 1990s, made patents easier to obtain while also making it more likely that patents will be enforced in the courts.[8]

When we look at the percent of patents awarded we fail to see the trend that Jaffe and Lerner suggest. In fact, the percent of applications granted hit a peak in

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[3] Ariel Pakes and Mark Shankerman, "The Rate of Obsolescence of Patents, Research Gestation Lags and the Private Rate of Return to Research Resources," in *R&D Patents and Productivity*, NBER Conference Series, Zvi Grilkiches eds, (Chicago: University of Chicago Press) 1984,

[4] M.J. Adelman, "The New World of Patents Created by the Court of Appeals for the Federal Circuit*,: University of Michigan Journal of Law Reform*," 20, 1987, 979-1007.

[5] Robert P. Merges and Richard R. Nelson, "On the Complex Economics of Patent Scope*," Columbia Law Review*, 90.

[6] S. Kortum and J. Lerner, "What is Behind the Recent Surge in Patenting," Research Policy, 1999, 28, 1-22 and S.; J.O. Lanjouw and J. Lerner, "The Enforcement of Intellectual Property Rights," *National Bureau of Economic Research Working Paper* #6296, 1997.

[7] S. Kortum and J. Lerner, "What is Behind the Recent Surge in Patenting," *Research Policy*, 1999, 28, 1-22.

[8] Adam B. Jaffe and Josh Lerner, *Innovation and Its Discontents: How Our Broken Patents System is Endangering Innovation and Progress and What To Do About It*, (Princeton: New Jersey, Princeton University Press), 2004

1966 and 1967 of 77% but this rate has generally been declining over time. In 2007, for example, it fell to 34% but rebounded to 45% in 2010.

II. Patent Time Periods and Types of Patents

In the United States the law provides for a specific time period for which the patentee enjoys exclusively. Utility patents provide protections for up to 20 years from the date of application. This time period was increased from 17 years from the grant date to 20 years from the application date by the "TRIPS" agreement. This is the agreement on Trade-Related Aspects of Intellectual Property Rights that was enacted in 1994 as part of the General Agreement of Tariff and Trade. There is some evidence that the extension of the patent duration periods may yield greater innovation in the economy.[9]

Other patents types, such as design patents, have shorter protection periods (14 years). The effective length of patent protection is often much shorter than the official length set forth in the law. Factors such as non-infringing innovation may result in a much shorter *effective* patent life.[10] O'Donoghue, Scotchmer and Thisee have showed that effective patent life is partially a function of patent breath.[11] They show that greater patent breath can have beneficial effects of enhancing innovation.

III. Probabilistic Patents and Patent Litigation

It is important to understand that patents really do not give the patent owner the right to exclude but merely the right to *try* to exclude others.[12] So in reality the actual scope of a patent is uncertain until it is litigated.[13] Part of this uncertainty comes from the filing process where patents incur minimal scrutiny by patent examiners.[14] In addition there is significant variability in the degree of scrutiny applied by different examiners.[15] Another source of uncertainty is that even if a patent is granted, it may be later challenged or infringed upon by competitors. The

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[9] David S. Abrams, Did TRIPS Spur Innovation: "An Analysis of Patent Duration and Incentives to Innovate," *University of Pennsylvania Law Review*, vol 157, 2009, 1613-1647.

[10] Mansfield and Levin et al.

[11] Ted O'Donoghue, Suzanne Scitchmer and Jacques-Francios Thisse, "Patent Breath, Patent Life and the Pace of Technological Progress," *Journal of Economics & Management Strategy*, 7 (1) Spring 1998, 1-32.

[12] Carl Shapiro, "Antitrust Limits to Patent Settlements," *Rand Journal of Economics*, 34 (2), 2003, 391-411.

[13] Mark A. Lemley and Carl Shapiro, "Probabilistic Patents," *Journal of Economic Perspectives*, 19 (2), Spring 2005, 75-98.

[14] Adam B. Jaffe and Josh Lerner, Innovation and Its Discontents: How Our Broken Patents System is Endangering Innovation and Progress and What To Do About It, (Princeton: New Jersey, Princeton University Press), 2004.

[15] Mark Lemley and Bhaven N. Sampat, "Examiner Characteristics and the Patent Grant Rate," *Stanford Law School Working Paper,* 2010.

patent holder then can try to pursue legal means to stop the infringement. Practically the enforcement of the exclusivity comes through litigation. However, only 1.5% of patents are ever litigated and only 0.1% ever go to trial.[16]

The law also provides that if another party infringes on the patent, damage remedies are potentially available.[17] However, in spite of enhancements in the legal protections to patent holders, a variety of factors influence the realistic protections patents actually give the patent holder. Patents are only as good as the perceived willingness and ability of the patent holder to protect its patent rights. This includes having the financial wherewithal to defend the patent including against defendants with “deep pockets.”

Patents reveal significant information to the market which may be able to utilize what has been revealed through the patent filing to create a competitive product that may legally “copy” some of the key attributes of the patented product. This is why it is not surprising that Mansfield has found that companies patented only approximately half of their potentially patented products.[18] Instead, companies may rely on more basic safeguards, such as secrecy, to protect their intellectual property.[19]

Mansfield also found that there was considerable variation across industries with respect to how important patents seem to be to companies. In some industries, such as pharmaceuticals and chemicals, the impact of patents was “very substantial.”[20] This is the case in the pharmaceutical industry where it is difficult, but not impossible, for competitors to invent around a new patented drug compound. However, Mansfield found that in a majority of industries companies report that patent protection was not a major factor in innovations being introduced to the market.

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[16] Jean O Lanjouw and Mark Shankerman, “Characteristics of Patent Litigation: A Window on Competition,” *Rand Journal of Economics*, 31 (1), 2001, 129-151.

[17] Patrick A. Gaughan, *Measuring Business Interruption Damages and Other Commercial Damages* (Hoboken, NJ: John Wiley & Sons), 2nd edition, 2009. 315-333.

[18] Edwin Mansfield, “Patents and Innovation: An Empirical Study,” *Management Science*, 1986, 32, 173-181.

[19] William Cohen, Richard Nelson and John P. Walsh, “Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (Or Not),” *National Bureau of Economic Research Working Paper* #7552, February 2000.

[20] Mansfield op cit.

IV. Patent Trolls and Patent Litigation

In recent years a new player in the patent litigation business has emerged – nonpracticing entities or what are pejoratively referred to as *patent trolls*. These are entities which have purchased patents but have never practiced and likely have no intention of practicing. Thus these entities are ones which derive most, if not all, of its revenues from licensing and enforcing the patents they owns. These firms make their money by suing other corporations for infringement.[21] Patent trolls do "not contribute to the specific goal the system was meant to serve: technological innovation."[22] While there is an active secondary market for patents, critics of troll contend that they are not involved in patent sales for the purposes of furthering innovation, but participate in the "more questionable market for the settlement of lawsuits involving weak, outdated or irrelevant patents."[23]

It has been reported that over 70% of patent litigation is filed by nonpracticing entities.[24] Other studies have traced the rising volume in patent lawsuits to the increased role of trolls.[25] Research has found that the gains being pursued by these nonpracticing entities are from being able to extract settlements. PricewaterhouseCoppers researchers found that damage awards for nonpracticing entities were more than double those of practicing entities.[26] However, other researchers found that nonpracticing entities were not overcompensated through royalties rates in licensing markets.[27]

It has been reported that over 70% of patent litigation is not filed by nonpracticing entities.[28] However, according to PatentFreedom, an organization that studies nonpracticing entities, 60% of nonpracticing entities are asserting patents that were originally assigned to them while, as of the middle of 2011, 25% of the nonpracticing entities surveyed were enforcing patents that they had acquired and this percentage has been rising.[29]

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[21] Ashby Jones, "When Lawyers Become 'Trolls', *Wall Street Journal*, January 23, 2012, page B1.
[22] Robert Merges, "The Trouble With Trolls: Innovation, Rent-Seeking, and Patent Reform," *Berkeley Technology Law Review*, 24 (4), 1583.
[23] Ibid
[24] "Tech Giants New Way to Thwart Patent Lawsuits*,*" *Bloomberg Business Week*, February 1, 2010.
[25] "A Closer Look: Patent Litigation Trends and the Increasing Impact of Nonpracticing Entities," *2009 Patent Litigation Study,* PriceWaterhouseCoopers.
[26] Ibid
[27] Jiang "Jack" Lu, "The Myths and Facts of Patent Troll and Excessive Payment: Have Nonpracticing Entities Been Overcompensated?", *Business Economics*, 47 (4), 2012, 234-249.
[28] "Tech Giants New Way to Thwart Patent Lawsuits*,*" *Bloomberg Business Week*, February 1, 2010.
[29] www.patentfreedom.com

While it is not the focus of our paper, we examine the trend in patent lawsuits to see if there was a pickup in the volume of litigation which could possibly be associated with the activities of the trolls. We also seek to determine if there is any discernible relationship between the volume of patent litigation and the overall cyclical variation in the economy. Lawsuits may also have some information content on the value or quality of patents. Allison et al theorized that higher quality or higher value patents are more likely to be litigated and renewed which involves payment of fees.[30] Perhaps higher quality or value patents are more likely to be initially granted while those which are lower value or quality patents ultimately do not get granted. However, as we have noted, this is not the focus of this paper but will be left for further research.

V. Research & Development and Patents

In some industries the research and development process can be quite time consuming and costly. For example, pharmaceutical companies may have to invest hundreds of millions of dollars to develop a new major drug. Grabowski estimated that the average cost of a new FDA approved drug was $802 million "for 1990s approvals."[31] Converting this to 2013 dollars yields a value easily in excess of one billion dollars. In addition, the vast majority of the drugs they research fail to yield an effective and approved drug. Moreover, the research, development and subsequent approval process may take as long as ten years. If companies did not have the ability to recoup such considerable investments over an extended time period, there would be little incentive to pursue the expensive development process. Thus, patent protection helps provide such incentives.

Economists have long studied patent statistics as a way of measuring the "inventiveness" of an economy.[32] For example, Pakes and Griliches found a strong relationship between the number of patents awarded and research and development expenditures.[33] The strength of this relationship between patents and R&D has been confirmed by other research.[34] In addition, Kortum and Lerner find that

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[30] John R. Allison, Mark A. Lemley, Kimberly A. Moore and R. Derek Trunkey, "Valuable Patents," *Georgetown Law Journal*, Vol. 92, p. 435, 2004.

[31] Henry Grawbowski, "Are the Economics of Pharmaceutical Research and Development Changing?" *Pharmaconomics*, 22 Supp. 2, 2004, 15-24.

[32] Zvi Griliches, Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature*, 28, December 1990, 1661-1707 and Zvi Griliches, Ariel Pakes and Bronwyn Hall, ":The Value of Patents as Indicators of inventive Activity," NBER Working Paper Series, #2083, November 1986.

[33] Ariel Pakes and Zvi Griliches, "Patents and R&D at the Firm Level: A First Look," in R&D Patents and Productivity, Zvi Griliches eds, University of Chicago Press, 1984,

[34] John Bound, Who Does R&D and Who Patents," *in R&D, Patents and Productivity*, Zvi Griliches ed, (Chicago: University of Chicago Press), 1984, 21-54.

increases in R&D productivity may have been a more important explanatory factor for the post-1982 increase in patents that happened to also coincide with the establishment of the Court of Appeals.[35]

VI. Data and Variables

The United States Patent and Trademark Office (USPTO) publish annual data on patent applications and patent grants. These data are organized by broad industry categories. We have gathered these data for the period 1950-2010. Over that time period there were 10.2 million utility patent applications of which 5.3 million were accepted for a 57.8% acceptance rate. However, as we have noted and as Figure 1 shows, the acceptance rate has been generally trending downward since the early 1970s when the rate in 1971 and 1971 was 75%. In 2007 the acceptance rate fell to 34% and by 2010 the rate rebound to 45% but still was well below the three quarters acceptance rate of the early 1970s.

Over the three decade period, years 1950-1989, patents granted grew at a faster rate than patent applications. For example in the 1950s, patents granted grew at an average annual rate of 3.8% compared to applications which grew at a 1.9% annual rate. In the sixties granted grew at a 3.5% compared to 2.4% for applications. In the 1970s, the annual growth rate of patents granted was a negative 2.6% compared to a slightly positive 0.2% growth rate for applications. We know the 1970s was generally a weak economic period and featured a serious recession and stagflation. In 1980s the annual growth of patents was still higher (7.6%) compared to 4.4% for applications. While there was a serious recession in 1982-83, there was a strong recovery in output and employments markets.

The relationship between the growth of patent applications and patents granted seems to change over the period 1990-2010. Here patent applications begin to grow more rapidly than patents granted with that differential becoming greater in the 2000s (5.4% applications compared to 1.2% granted). These decade averages raises some questions about the linkage between patent applications and overall economic growth that can only be answered by a more rigorous time series analysis of the annual data.

Our data set precedes the 2011 federal patent reform act, the Leahy-Smith America Invents Act, which took effect March 16, 2013. This law changed the "first to invent" system that the USPTO followed for decades to a "first to file"

[35] Kortum and Lerner, 1998. op cit.

system. Under the new law the USPTO would give priority to those who were first file even if they were not the first to come up with the idea. From an empirical perspective, the implementation of the law led to a flood of applications in the first quarter of 2013. However, given our cut off year of 2010, our data set is unaffected by this change in the law.

Figure 1: Utility patent acceptance rate

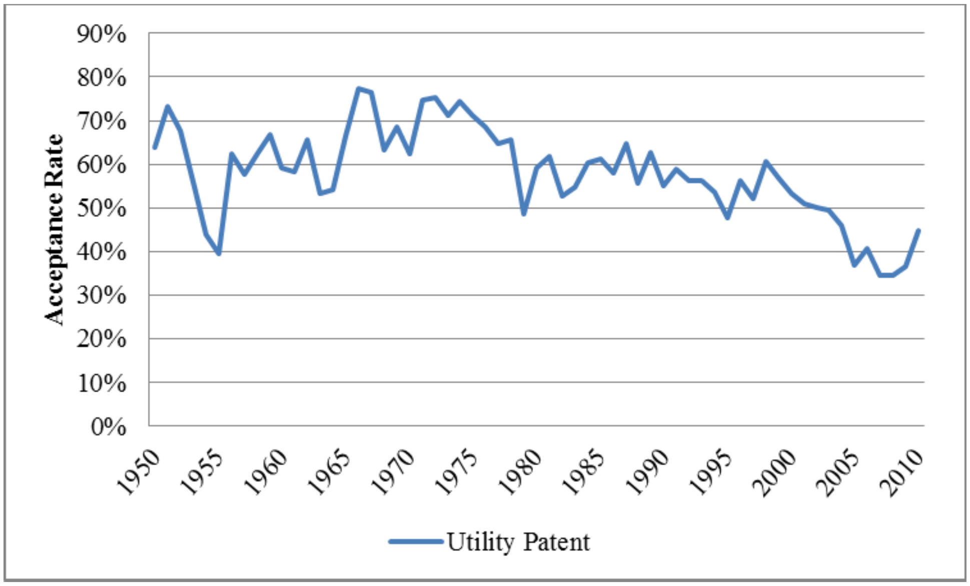

Table 1 shows that 31% of the patents granted are in the “Computer and Electronics” industry. In recent years this percentage has been higher. For example, in the years 2001 -2010 Computers and Electronic accounted for 45% of the total. Over the full study period (1950-2010), “Machinery” accounted for 19% of total patents granted while the next largest category was “Chemicals” which accounted for 13% of the total. This percentage increased in the 2000s as in prior decades it had been around 10%-11%. As Table 1 shows, no other category comprised more than 10% of the total patents awarded.

Table 1: Percent Distribution of Patents Granted by Industry: 1950-2010

Industry	*% of Total*	*Cumulative Total*
NAICS 334. Computer and electronic products	31.17%	31.17%
NAICS 333. Machinery	19.25%	50.42%
NAICS 325. Chemicals	13.36%	63.79%
NAICS 332. Fabricated metal products	7.46%	71.24%
NAICS 335. Electrical equipment, appliance, and components	7.13%	78.38%
NAICS 339. Miscellaneous manufacturing	7.08%	85.46%
NAICS 336. Transportation equipment	4.91%	90.37%
NAICS 326. Plastics and rubber products	4.05%	94.42%
NAICS 327. Nonmetallic mineral products	1.71%	96.13%
NAICS 313-316. Textiles, apparel and leather	1.13%	97.26%
NAICS 331. Primary metals	0.80%	98.07%
NAICS 322,323. Paper, printing and support activities	0.65%	98.72%
NAICS 337. Furniture and related products	0.45%	99.17%
NAICS 311. Food	0.44%	99.61%
NAICS 321. Wood products	0.25%	99.86%
NAICS 312. Beverage and tobacco products	0.14%	100.00%
All industries (total)	100.00%	

VII. Macro Explanatory Variables

While there has been much research over many decades on patents as indicators of innovation, our study has a different focus. We focus on how the volume of patents awarded in the United States has varied as a function of the cyclical variation of the macroeconomy. As macroeconomic explanatory variables we utilize real gross domestic product (GDP), as well as the consumer price index, yield on ten year treasuries as well as expenditures on research and development. A list of these variables is shown in Table 2 below.

Table 2: Macroeconomic Variables, 1970-2010 (annual)

Macroeconomic Variables	*Source:*
GDP = the real GDP indexes in billions of chained 2005 dollars (annual)	Bureau of Economic Analysis
CPI = consumer price indexes(Base Period:1982-1984=100)	Bureau of Labor Statistics
Resdev = research & development expenditures	National Science Foundation
Bond = market yield on U.S. treasury securities at ten-year federal reserve	The Federal Reserve
Unem = unemployment rate	Bureau of Labor Statistics

In examining the relationship between the number of patents and possible macroeconomic deterministic variables we need to be mindful that prior research implies that this relationship may have some complex aspects. However, the basic general expected relationships are set forth below:

$TN = f\ (GDP, R\&D, Bond, Inflation)$

$\partial\ TN / \partial\ GDP > 0$

$\partial\ TN / \partial\ R\&D > 0$

$\partial\ TN / \partial\ I\ Rates < 0$

$\partial\ TN / \partial\ Inflation\ \geq 0$
$<$

$\partial\ TN / \partial\ Unem\ < 0$

We expect that there is a positive relationship between the broad macroeconomic aggregate GDP and expect a similar sign for the relationship between R&D and patents as some R&D will lead to more patents. In fact this is what earlier research by Pakes and Griliches as well as Bound have found using only much older data. However, we also expect there will be "leakage" in this relationship as a percent of R&D may not lead to anything that is patentable. In addition, there is evidence that patent recipients engage in strategic behavior such as by assembling "portfolios" of patents which may yield different benefits such as to preempt other potential patentees. Thus one patented product could result in multiple patents. Some researchers have found evidence that such strategic behavior is particularly prevalent in certain industries such as the semi-conductor industry.[36] To the extent that such behavior exists, it may not change the direction of the relationship between R&D and total patents, or even that between GDP and total patents, but it could affect the lagged relationship between the variables if the strategic behavior takes place with a lag after the filing of the original patent.

We expect an inverse relationship between interest rates and patents as an increase in interest rates may raise the costs of capital and the cost of investment. When this occurs, ceteris paribus, it could reduce the output of total investment activity thereby reducing the number of patents. The relationship between patents and inflation is less obvious as an argument could be made for higher prices giving an incentive but also a disincentive to pursue patents.

As we will see, our empirical results confirm these apriori expectations although the impact of interest rate variation will be seen in the error correction term while the impact of GDP and R&D will be apparent directly in the coefficients of these variables. As expected we will see that inflation is not significantly related to patents. We will discuss further these and other results after we elaborate on our methodology.

VIII. Empirical Methodology

We take as a starting point the existence of a vector autoregressive (VAR) model describing our variables. This is a standard approach used in the empirical analysis of time series data (see e.g. Hamilton (1994).[37] In particular, and as we have discussed, the variables that we are interested in examining can be gathered into a vector by defining:

$$Y_t = (app_t, gra_t, gdp_t, bond_t, suits_t, resdev_t, cpi_t)',$$

[36] Bronwyn Hall and Rosemarie Ham Ziedonis, "The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. semiconductor Industry, 1979-1995, *RAND Journal of Economics*, 32 (1) Spring 2001, 101-128.
[37] James D. Hamilton, *Time Series Analysis*, (Princeton, New Jersey: Princeton University Press, 1994.

where app_t = number of patent applications, gra_t = number of patents granted, $suits_t$ = number of lawsuits filed, and $\{gdp_t, bond_t, cpi_t\}$ are macroeconomic variables (i.e., real GDP, the interest rate on 10 year government Treasury bonds, and the consumer price index, respectively). Now, define $y_t = \log(Y_t)$, except for the interest rate variable, which remained in levels in y_t. The VAR *(p)* model, where *p* denotes the number of lags, that we use to describe the dynamic behavior of these variables is:

$$y_t = \alpha + \sum_{i=1}^{p} \Gamma_i y_{t-i} + \Pi x_t + \varepsilon_t,$$

where α is a vector of intercepts, Γ_i is a conformably defined matrix of constants, Π is a matrix of constants associated with exogenous variables, x_t (in our subsequent empirical analysis, we set x_t = various lags of the unemployment rate, $unem_t$, as well as other macroeconomic variables, to be discussed in the sequel).

Now, given that all of the variables in y_t are nonstationary, in the sense that they are integrated of order 1 (i.e., they are so-called *I(1)* variables, using the terminology of Granger, as discussed in Hamilton (1994), standard statistical inference cannot be carried by fitting regression models to the variables in y_t and simply looking at *t*-statistics and standard goodness of fit measures such as the $\overline{R}^2$ statistic. In light of this, and in order to address the issue of nonstationarity (and associated problems associated with so-called spurious correlation, as discussed in Granger and Newbold (1974) and Engle and Granger (1987)), a standard approach is to model the growth rates of the variables in Y_t.[38] By taking growth rates, all problems of nonstationarity and spurious correlation are removed, and standard regression models can be fit and inference carried out. Moreover, growth rates have a natural economic interpretation, and are clearly understood by both applied practitioners and policy makers.

In the current context, taking growth rates leads to a model of the form:

$$\Delta y_t = \alpha + \sum_{i=1}^{p-1} \zeta_i \Delta y_{t-i} + Bz_{t-1} + \Pi x_t + \varepsilon_t,$$

where all elements of Δy_t are in growth rates, except the yield variable, which is in

[38] Clive W. J. Granger and Paul Newbold, "Spurious Regressions in Econometrics," *Journal of Econometrics*, Elsevier, vol. 2(2), July, 1974, 111-120. R. F. Engle and Clive W. Granger, "Cointegration and Error Correction: Representation, Estimation and Testing, *Econometrica*, 55, 1987, 251-276.

differences. Note also that since Δy_t is assumed to be *I(0) (* i.e., stationary), then y_t is *I(1)* (i.e., nonstationary, such that its first difference is stationary). Evidently, Δy_t is a *1* x *7* vector. Moreover, z_{t-1} is assumed to be a *1* x *r* vector of *I(0)* variables, with $0 \le r < n$, and *B* is an *n* x *r* matrix of constants.[39] The other components of this model are defined above.

This model is a so-called vector error correction (VEC) model, and the variable z_t is a so-called error correction variable. Namely, this is a cointegration model, and cointegration enters into the system via the inclusion of the variable z_t. Here, cointegration exists if $B \neq 0$ *and* z_{t-1} is a vector of *I(0)* variables. In general, there can be either no cointegration (i.e., *B=0)* or there can be cointegration (i.e., $B \neq 0$). Moreover, as discussed in Hamilton (1994), if there is cointegration, then the variable z_t is defined as follows:

$$z_t = A' y_t,$$

where A is a *1* x *r* matrix of constants , and *r* is the so-called *rank* of the *cointegration space.* If $r > 0$, then it is clear that z_t is actually a vector of *r* different error correction variables, *and* each of these variables is simply a unique linear combination of variables in y_t. Moreover, z_t is stationary (i.e., *I(0)*), as discussed above. In sum, stationary error correction variables are constructed by forming (unique) linear combinations of nonstationary *I(1)* variables (the y_t). In general, there is no reason why linear combinations of nonstationary variables should be stationary. Cointegration does not generally arise, but is rather a result of a "unique" long-run relationship resulting in the existence of so-called *common stochastic trends* linked *I(1)* variables. From an economic perspective, cointegration is interesting, as variables that are "cointegrated" (i.e., the variables used to construct z_t), are linked in a very special way, such that they never "drift" too far apart over time, for example. For a complete discussion, refer to Engle and Granger (1987) and Hamilton (1994).[40]

Our objective is to fit regression models of the type $\Delta y_t = \alpha + \sum_{i=1}^{p-1} \zeta_i \Delta y_{t-i} + B z_{t-1} + \Pi x_t + \varepsilon_t$. In particular, we focus on two equations from

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[39] In the next section, we provide empirical evidence that all variables constituting Δy_t are indeed *I(0).*Additionally, we establish that z_{t-1} is comprised on *I(0)* variables.

[40] Engle and Granger, 1987 and James Hamilton 1994.

this system of 7 equations. Namely, we fit models of app_t and gra_t. Lags are selected using the Schwarz information criterion (SIC), and via examination of the statistical significance of regression coefficients. Cointegration is tested for using the Engle-Granger 2-step cointegration test discussed in Hamilton (1994). Finally, Granger causality is tested for via the examination of the statistical significance of coefficients associated with lagged regressor appearing on the right hand side of the model. For example, if lags of GDP are found to be significant in one of our models, then we conclude that there is evidence of Granger causality from GDP to either app_t and gra_t.

IX. Empirical Findings

In order to test for nonstationarity of the variables included in our regression models, we ran a series of augmented Dickey-Fuller unit root tests. The results of these tests, summarized in Table 3, indicate that all of our variables are *I(1)*, with the exception of *unem* (which is *I(0))*, and *cpi (*which is *I(2)).*[41] This is as expected, for all variables other than *bond,* and *cpi*, for which empirical evidence on this issue in the literature is mixed. In particular, while finance theory suggests that *bond* must be *I(0),* it is not unusual to find empirical evidence in favor of the variable being *I(1)*. In our empirical experiments, it suffices to assume that the variable is *I(1)*, as the variable is only included as a potential explanatory variable in our error corrections variables (it is otherwise statistically insignificant in all of our models) , and assuming that the variable is *I(0)* would simply result in the probability limit of any weight associated with *bond* in our error correction variables being 0. With regard to *cpi*, we find no evidence of the importance (statistical significance) of this variable in our regression models, and hence and concern about whether it should actually be modeled as *I(1)* or *I(2)* is moot.

[41] Select variables from Table 1 are plotted in Figures 2 and 3.

Table 3: Unit Root Tests for the Sample Period 1950-2010

	Unit Root Test in Logs		*Unit Root Test in Differences*	
Variable	*lags*	*ADF stat*	*lags*	*ADF stat*
App	0	2.273	0	-7.013*
Gra	0	-0.254	0	-9.507*
Suits	0	0.336	0	-7.257*
Gdp	0	-2.162	0	-6.885*
Resdev	1	-2.466	0	-3.557*
Unem	1	-3.081*		
Cpi	1	-0.147	2	-2.148
Bond	0	-1.465	0	-6.321*

Notes: Augmented Dickey-Fuller (ADF) test regressions were carried out by fitting the model
$\Delta v_t = \alpha + \beta_0 v_{t-1} + \sum_{j=1}^{l} \beta_j \Delta v_{t-j} + \eta_t$, *for the entries under the header "Unit Root Test in Logs". Here,* Δv_t *denotes the difference of the log of one of the variables in the first column of the table, except for the variables unem and bond, for which logs were not taken. Additionally,* α, β_0, *and* $\beta_j, j = 1,....,l$ *are constants, and* η_t *is an error term. Lags, l, are selected using the SIC. The null hypothesis of the test reported as "ADF stat" is*
$H_0 : \beta_0 = 0$*, and corresponds to a finding of nonstationarity. Starred entries denote rejection of the null hypothesis at a 95% significance level. Entries under the header "Unit Root Test in Differences" are analogous to those under the header "Unit Root Test in Logs", except that differences of the variables were first taken. Thus, variables found to contain at least one unit root (i.e., all variables under the header "Unit Root Test in Logs" that are not starred) are marked with a star under the header "Unit Root Test in Differences" are I(1).*

Turning now to our regression models, recall that we fitted models of the form $\Delta y_t = \alpha + \sum_{i=1}^{p-1} \zeta_i \Delta y_{t-i} + B z_{t-1} + \Pi x_t + \varepsilon_t$ to app_t and gra_t. Our findings are summarized below. Note that variables with a ** denote variables with coefficients that were found to be statistically significantly different from zero, at a 95% level of confidence, while those with a * are significant at a 90% level of confidence. Additionally, statistics with a †† indicate rejection of the null of non-cointegration (i.e., indicate a finding of cointegration) at a 95% level of significance.[42]

Number of Patent Applications

$$\Delta \log app_t = 0.024 + 0.157\Delta \log app_{t-1} + 0.183\Delta \log gdp_{t-3} - 0.054\Delta \log resdev_{t-3} + 0.125\Delta \log suits_{t-2} - 0.098 z_{t-1}$$

$\overline{R}^2 = 0.055$, DW=2.071, Sample Period = 1957 - 2010,

$$z_{t-1} = \log app_{t-1} - 3.484 - 0.970 \log gdp_{t-1} - 0.037 \log resdev_{t-1} + 0.073 bond_{t-1}$$

$$\hat{\tau} = -3.789^{\dagger\dagger}$$

Number of Patents Granted

$$\Delta \log gra_t = -0.033 - 0.144\Delta \log gra_{t-1} + 1.105\Delta \log gdp^{*}_{t-3} + 0.302\Delta \log resdev_{t-3} + 0.372\Delta \log suits^{*}_{t-2} - 0.387 z^{**}_{t-1}$$

$\overline{R}^2 = 0.257$, DW=1.843, Sample Period = 1957 - 2010,

where:

$$z_{t-1} = \log gra_{t-1} - 3.208 - 1.089 \log gdp_{t-1} + 0.105 \log resdev_{t-1} + 0.041 bond_{t-1}$$

$$\hat{\tau} = -5.108^{\dagger\dagger}$$

A number of clear conclusions emerge upon inspection of the above empirical results, all of which are summarized below.

(1) The error correction variables from each equation are *I(0)*, indicating the presence of cointegration in the data. This finding is supported by the values of the cointegration test statistics (i.e., the statistics reported above, which are equal to -3.789 - patent applications; and -5.108 - patents granted). Both of these statistics indicate a rejection of the null hypothesis of "no cointegration" using a one-sided test at a 5% level. The implication of this finding is that there is a "long-run" stochastic trend underlying the dynamic behavior of both patent applications and patents granted with real GDP and R&D.[43] However, it should be noted that this relationship is likely only useful for forecasting patent applications (or patents granted) if the error

[42] Note that the statistic is obtained by carrying out an augmented Dickey-Fuller test of the variety discussed in the footnote to Table 1, except that there is no intercept in the test regression, and that the left hand side variable is the residual from a regression of app_t (gra_t) on gdp_t, $resdev_t$, $bond_t$, and an intercept. In this sense, is the test statistic associated with an Engle-Granger 2-step cointegration test, as discussed in Engle and Granger (1987).

[43] Our error correction variables also include the bond yield on 10-year Treasuries. However, as bond yields are arguably stationary (in theory), this empirical finding is not the focus of our discussion.

corrections variable in question is significant in the accompanying model of growth in patent applications (patents granted). As discussed below, the error correction variable is only significant in our model of the growth in patents granted.

(2) The only error correction variable that is statistically significant is the one in the model of the number of patents granted. The error correction variable in the model of the number of patent applications is not significant. This finding suggests that any "gains" (in forecasting growth in the rate of patents granted) associated with the specification and use of long run error correction variables is likely to be found only in the context of predicting growth in patents granted. It also underscores the futility, though, of trying to predict patent application growth using our explanatory variables, as discussed below.

(3) There are no significant variables in the regression fitting number of patent applications against various variables.[44] In particular, *no* variable is statistically significant in our model of patent application growth. This is not surprising, given the low $\overline{R}^2$ of only 5.5% in that model.[45] This means that none of our explanatory variables are useful for forecasting patent application growth, and that patent application growth does not appear to be linked to the business cycle or suits filed.

(4) Both real GDP and the number of patent suits filed are statistically significant in the model of the number of patents granted. Moreover, the $\overline{R}^2$ goodness of fit statistic is 26% for our patents granted model. This is significantly higher than the value of 5.5% noted above for our model of patent application growth. This finding suggests that growth in the number of patents granted is linked with our macroeconomic variables, and in particular with real GDP, even though the same cannot be said in the case of growth in patent applications. One implication of this interesting finding is that it may be preferable for firms to submit new patent applications during

[44] As discussed above, our specification search involved "trying" a variety of variables, including unemployment and CPI inflation, as well as various lags of all variables listed in Table 1. Additionally, various other variables, including a spread between 10 year and three month bond yields and aggregate U.S. research and development were also examined. All variables that were statistically insignificant were dropped from our models, with the exception of the three key variables appearing in both of our models, which, while not significant in both models, were included in order to make our models "comparable" with each other.

[45] The $\overline{R}^2$ is a robust measure of the percentage of variation in the growth rates being modeled that is "explained" by the explanatory variables in our models.

periods of increasing economic growth (i.e., during expansionary phases of the economic business cycle). For a visual representation of the growth rates modeled, refer to Figure 2.

(5) Research and development (R&D) is not significant in either model. However, in the model of patents granted, the variable has a coefficient of 0.302, which would be found to be significant, were a *t*-test with size equal to 0.25 used. Thus, while not significant at a 90% level of confidence, it is significant at a 75% level of confidence. Moreover, recall that Clive W.J. Granger, the Nobel prize winning forecast researcher in the area of forecasting over the last five decades of his life, suggested in a number of writings that, when deciding whether to include explanatory variables in forecasting models, using a level of 5% is not necessarily optimal, and he instead recommends the "looser" test level associated with a *t*-statistic value of 1.0.[46] In the case of R&D in our patents granted equation, the *t*-statistic associated with R&D is 1.177. Thus, we have weak evidence that growth in patent applications granted responds positively not just to real GDP and suits filed, but also to R&D expenditures, as might be expected.

(6) In addition, the sign of the coefficients associated with GDP, suits filed and R&D are all positive in the model of the number of patents granted. In the case of R&D and GDP, this finding is as expected. Namely, increases in the growth rates of either GDP or R&D lead to an increase in the number of patents granted, likely due to an increase in the overall rate of applications (relative to the standard increase in applications due to the trend in applications, as can be observed in Figure 3).

(7) There is Granger causality from real GDP growth to the number of patents granted.[47] This result is predicted on the fact that real GDP growth is significant in our model of the growth in patents granted, and that it enters in with a lag of 3 years. Namely, and in accord with the definition of Granger causality, past changes in the growth rate of real GDP lead to increases in the future rate of growth in patents granted. If we adopt the *t*-statistic critical value of 1.0 discussed above, then we see that there is also Granger causality from R&D to the rate of growth of patents granted, and from the growth in

[46] See Clive W. J. Granger, "Outline of Forecast Theory Using Generalized Cost Functions," *Spanish Economic Review*, 1999, Springer, 1, 161-173.
[47] Clive W. J. Granger, "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica*, 37, 1969, 424-38.

suits filed to the rate of growth of patents granted. As may be inferred from our above discussion, there is no Granger causality from any variable to the rate of growth in patent applications.

(8) As a final observation, it is interesting to note that the first lag of the dependent variable, appearing as an explanatory variable in each model, is insignificant. This means that there is no clear "autoregressive" structure in (growth of) patent applications of patents granted. This is perhaps not surprising in the case of patent applications, given our previous observation of the very poor fit of that model. However, this is perhaps surprising, in the case of patents granted, given that the $\bar{R}^2$ goodness of fit statistic is 26% for this model. Evidently, we can explain patents granted growth rates using *other* variables (i.e., real GDP, etc.), and using the stochastic trend implied via inclusion of our error correction variable (recall that the error correction variable is constructed as a linear function of the log of lags in patents granted, real GDP, R&D and bond yields), but not directly using the lags of patents granted growth rates. This is related to the fact that "long-run" patents granted numbers are increasing over time (see Figure 3), so that past log level numbers do matter; even though past growth rates do not. As final evidence of the fact that past growth rates of patents granted are not useful, note that the Durbin-Watson (DW) statistic reported for our patents granted model is 1.843, corresponding to a finding of no first order autocorrelation in the residuals from the model.

Figure 2: Growth rates of patents granted and selected other variables, sample period: 1950-2010

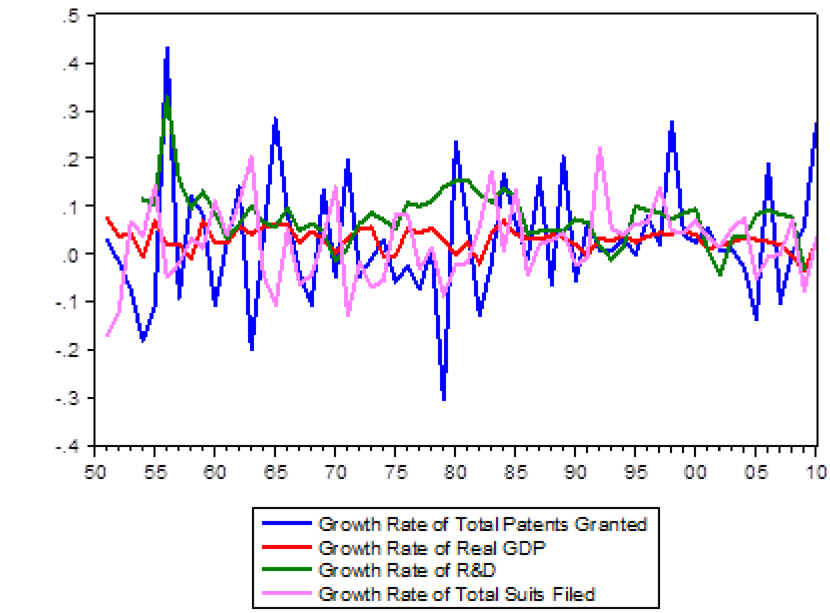
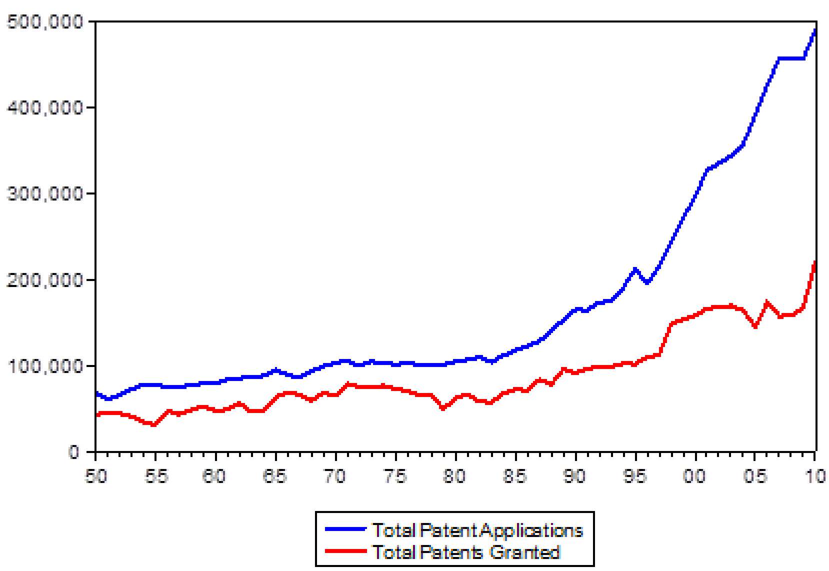


Figure 3: Patent applications and patents granted for the period 1950-2010



(9) We note that in recent decades the rate of growth of patent applications has surpassed that of patents granted. For example, the average annual rate of growth of patent applications was stagnant in the 1970s (0.2%), a period of weak economic growth, but rose to 4.4% in the 1980s and 6.1% in the 1990s. Patent application annual average growth remaining strong in the 2000s (5.4%). However, real GDP growth was relatively stable at approximately 3.2% over this three decade period. During this period we had two severe recessions (1973-75 and 1981-82) but also some robust expansions in the 1980s and 1990s. While applications were rising more rapidly than that which could be explained by the variation in the economy, the patent acceptance rate fell during this period from 67% in the 1970s to 59% in the 1980s, 55% in the 1990s and 43% in the 2000s. This decline in the acceptance rate helped allow patents granted to maintain a more stable relationship with the overall growth on the economy. The decline in the acceptance rate also may offset any *gaming behavior* by applicants seeking additional patents that what were warranted by the validity of the underlying applications.

X. Conclusion

We examine the extent to which U.S. patent applications and patents granted respond to the cyclical variation of the U.S. economy. We also analyze the extent to which other major macroeconomic variables, such as interest rates, inflation and research and development expenditures, are related to patent applications and grants. We find a relationship between major macro variables such as GDP and patents granted but not applications. In particular we find that both patent applications and patents granted are cointegrated with GDP and research and development indicating a long run stochastic relationship among these variables. However, our error correction variable in significant only in the patents granted model not the one with patent applications. In addition, we find that research and development expenditures are related to patents granted although the relationship with patents granted is weaker than with real GDP.

We do find Granger Causality from the growth in real GDP to the number of patents granted. In particular, our findings show that past change in the growth rate of real GDP leads to increases in the future rate of growth of patents granted.

Our regression models do not show a statistically significant relationship between patent applications and the explanatory variables but they do show such a relationship in the case of patents granted. This finding confirms our apriori expectations. It seems the patents that end up being granted are, in part, driving by broad economic factors whereas patent applications, which may partly reflect factors such as gaming behavior, is not so influenced. With respect to explanatory variables such as interest rates and inflation, we do not find any significant relationship with either patent application or grants. At least with respect to inflation, this is also consistent with our expectations.