Technology Transfer and the Business Cycle: Evidence from Patent Reassignments

Carlos J. Serrano*

University of Toronto and NBER

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Abstract

We propose a direct measure of technological change based on the transfer of the ownership of patents that are recorded at the United States Patent and Trademark Office (USPTO). The new indicator addresses two potential problems that previous patent statistics have had in the analysis of the short-run effects of technological change. First, while there might be long delays between the patenting of an invention and its use or commercialization, the date of the transfer decision is directly linked to its usefulness and demand through the market for patents. Second, while the use of patent counts has been critized because the economic significance of many individual patents is very low and variable, traded patents are both highly cited and less likely to be allowed to expire than the not previously traded ones. Next, we assess the

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relationship of the new indicator with changes in real GDP, total factor productivity, and R&D expenditures.

1 Introduction

One of the most important research questions faced by economists is what are the sources of business cycle fluctuations in employment, capital and investment. Standard real business cycle theory suggests that business cycles are a result of unexpected changes in the level of technology used in the economy. However, whether technology shocks create or destroy jobs in the short run is a heated theoretical and empirical debate.[1] While the theories and studies might seem reasonable, the problem is that it is hard to measure technology, technology shocks and their diffusion through the economy.

In this paper we contribute to the literature of measurement of technology by proposing a direct measure of technological change. The new indicator is based on the transfer of the ownership of patents that are recorded at the United States Patent and Trademark Office (USPTO). Next, we use the measure to make sense of the sources of business cycle fluctuations. In particular, we assess the relationship between the transfer of technology with changes in real GDP, total factor producitivity, and R&D expenditures.

The new indicator addresses two potential problems that made controversial the use of patent data in the analysis of the short-run effects of technological change. First, while there might be long delays between the patenting of an invention and its use or commercialization, the date of the trading decision is directly linked to the usefulness and demand for an invention through the market for patents. In this context, we argue

[1] Standard business cycle theory implies a positive correlation between technology shocks and hours worked. Gali [12] shows that a model with monopolistic competition, sticky prices and variable effort can explain the near zero uncorrelation between productivity and hours. Moreover, using SVAR model, he shows that positive technology shocks can generate a negative comovement between productivity and hours. Chari, Kehoe and McGrattan [6] criticizes Gali's SVAR framework. A more recent view is that business cycle fluctuations may be driven by a news shock, an innovation in agents expectations of future technological opportunities that arise before these opportunities are actually productive in the market (Beaudry and Portier [3][4]).

that patents are sold to firms with complementary assets and patent portfolios because unexpected changes in technology make some technologies and patent pools useful for the production process. Second, while the use of patent counts has been critized because of the economic significance of individual patents is very variable, traded patents are both more highly cited and less likely to be allowed to expire than the not previously traded ones. For these reasons, the transfer data is useful to study the kind of technologies and technology shocks associated to standard business cycle models: shocks that occur when output is affected, but not necessarily when the R&D and the patent application or granting decision take place.

We find that the transfer of technology is procyclical, i.e., the rates of growth of GDP are positively correlated with a business-cycle measure of the transfer of patents. The time-varying business cycle measure cannot be possibly uncovered by a direct inspection of the raw data because the decision to transfer a patent does not only depend on the business-cycle effects, but also on the specific characteristics of the stock of active patents available for transfer (e.g., average age, patent category, patent cohort (i.e., application year), etc).[2] We obtain such a measure estimating a binary-choice model of the decision of a patent being traded on patent characteristics such as age, patent category and patent cohort. The approach allows us to separately identify the business-cycle from the patent's life-cycle effects. We estimate the time year and age dummies using variation of the stock of patents available for being traded and the ones actually traded along the cross section and time series of the panel data set. The patent cohort effects are identified using variation in the number of years between the application and grant date of patents.

Understanding the sources of business cycle fluctuations and more specifically the role of the transfer of technology is important for economic policy and for determining which models are consistent with the data. To the extent that ideas are intermediate inputs in a production process, the reallocation of ideas to a better use can affect the level of

[2]For instance, younger patents are more likely to be traded than their older counterparts and the characteristics of the stock of active patents changes over time (Serrano [21]).

employment, the reallocation of labor, wages and output. Furthermore, since ideas are also an input in the research process, the reallocation of technology and intellectual property assets can carry important economic consequences associated to the long-run prospects of technological change. For instance, when innovation is cumulative it matters who owns the intellectual property rights. The incentives on research of subsequent inventors might be affected by the willingness to license or sell the patents when innovating around them is difficult.

The rest of the paper is organized as follows: Section 2 reviews the previous literature. Section 3 presents and discuss the data sample we use. Section 4 shows the empirical analysis and documents the patterns we find. And section 5 concludes the paper.

2 Literature review

There are two strands in the literature on identifying technology shocks: direct and indirect measures of technology. The first strand focused on direct measures of technology. It uses information on patents and research and development expenditures (see Griliches [13] and Shea [18]), patent citations[15], and more recently the publication of books in the field of technology (Alexopoulos [1]). The second strand is somewhat more indirect when measuring technology shocks. A common approach is to use long-run restrictions in a VAR framework to identify technology shocks (Gali [12], Francis and Ramey [11], Christiano, Eichenbaum and Vigfusson [7], Altig, Christiano, Eichenbaum and Linde [2] and Fischer [10], etc.). Alternatively, Basu, Fernald and Kimball [5] propose to measure the solow residual after controlling for non-technological effects such as imperfect competition, increasing returns, etc.

Shea [18] argues that using nondirect measures of technology can rise some issues. One is that in a SVAR framework the results depend on the assumption that technology shocks are the only variable that effect long-run productivity. For instance, the assumption does not hold if there is endogenous growth (Alexopoulos [1]) and the allocation of patent property rights can affect long run productivity (Merges and Nelson [16], Scotchmer [17], Green and Scotchmer [14]). The second one is that direct measures might be better linked to technological change. For instance, available data require a SVAR with a small number of lags and such a VAR is a poor approximation to the model's VAR (Chari, Kehoe and McGrattan[6]).

One way to get around some of these problems is to have direct measures of technological change. One popular indicator is the use of patent statistics. This has been done by many (see Griliches [13] for a survey and Shea [18] using this statistics to quantify the impact of technology shocks in a VAR framework). There are, however, some important criticims to the use of patent data to study short-run technological change fluctuations: 1) There is a non-trivial lag between the date a patent is applied or granted and the date when the innovation used or commercialized. The latter is particularly relevant since anecdotal evidence suggests that most of innovations protected by patents are never really implemented. Similarly, there might be a lag as well between the R&D expenditures for a certain innovation and their impact in production. 2) The absolute number of patents granted or applied tends to be noise measure because ther quality or importance of individual patents varies very much. For instance, only 22% of individually owned patents are renewed after their 13th year since their grant date (Serrano [21]). A more recent interesting indicator is the use of book publications on technology as recorded in the U.S. Library of Congress (Alexopoulos [1]). Alexopoulos finds that in response to a technology shock GDP, employment, and TFP increase, but technology shocks can only explain a small amount of the variation in employment. Obtaining that the result on employment is modest, it is not entirely surprising. It would be interesting to look at the Alexopoulos indicator weighted by the number of units published or sold. The distribution of books revenue as well as the distribution of patent value are very skewed. In this respect, the current indicator shares with existing patent statistics the criticism that there is a large variance in the importance of books and consequently the impact of the indicator might not be well capture by absolute numbers of titles.

3 Data

We use a panel of the histories of transfer and renewal decisions of individually owned patents. The panel contains patents granted from 1975 to 2000; and transfers of patents recorced at the USPTO between 1982 to 2001. Every patent is has its application date and year (i.e., cohort), patent aggregate technology fields (i.e., patent category) and the date that was transferred. The dataset allows us to study the life-cycle and business-cycle determinants of the trading decision.

The transfer data we use have been compiled by Serrano [21] using transactions of the ownership of patents that were recorded at the USPTO. Each transaction in the original patent reassignment records has a unique identifier, the patent numbers contained in the transaction, the name of the buyer and seller, and the date that the transfer was signed and recorded at the USPTO.[3] The patent numbers allowed Serrano to match the reassignment records to existing data on patent characteristics and patent citations (Hall, Jaffe, and Tratjenberg [15]). Similarly, Serrano also linked the records to the renewal status of patent using the Maintenance Fees Database supported by the USPTO.

In this paper, we focus on a sample of patents individually owned by inventors. The benefit is that individual owned patents are not subject to mergers or acquisitions unlike patents owned by large corporations. In addition, individual inventors are interesting on its own shake: they represent about 20% of all granted U.S. patents, and individual entrepreneurship has been an important aspect of the contemporary history of inventions in the U.S.

There are a number of issues that Serrano looked in detail when constructing the data.

[3]An assignment, as defined by U.S. patent law, is a written document that acknowledges the transfer by a party of all or part of its right, title, and interest in a patent or patent application.

For instance, whether a patent transactions is recorded because an administrative event such as the change of name, security interest, etc. He also identifies whether a recorded assignment is a first assignment (i.e., between an employee and the firm that works for) or a reassignment (i.e., a transfer between individuals or firms).

Two new issues we must deal with are the following. First, we consider transactions where the seller is an individual owner. Since after a patent has been sold, we cannot identify who is the buyer, patents not only the patent must be granted to an individual, but also that the seller of the patent must be an individual. Since the data does not keep track of the ownership of the patent, to operanationalize the objective we restrict attention to transactions in which the name of the seller coincides with the name of the original inventor.[4] The details of the rest of procedures used to deal with the reassignment records were explained in detail in Serrano [21].

4 A Measure of Technological Change: the Transfer of Patents

The new indicator is based on data on the transfer of patents. The transfer data addresses two potential problems that have faced previous patent based measures of technological changes such as the absolute number of patents grants and applications. One is that the importance of individual patents varies very much. A second problem is that the commercialization of an innovation can be years after the patent has been granted or applied for, and the number of years between the application and the grant date varies significantly among patents. In the transfer data, however, traded patents are highly cited and less likely to be allowed to expirethe date and the intensity of the transfer of patents captures the actual demand for the patent services and the technologies that they protect.

[4]If there is more than one inventor, then we consider that it concides at least with the name of one of them.

The demand for specific patents is an important determinant of the transfer of patents, but the transfer also depends on the characteristics of the stock of active patents. The new indicator should not be affected by changes in the composition of the characteristics of the stock of patents in the number of patents such as the age of patents, their patent category and cohort. This is important because both younger and highly cited patents are more likely to be traded and that the transfer rate across patent categories can be significantly different (Serrano [21]).

One way to deal with the composition of the stock of patents is to estimate a logit model of the probability of an active patent being traded. The logit framework allows us to control on a number of patent characteristics. In particular, we regress the likelihood of a patent being traded on time dummies and observable patent characteristics such as their age, patent category, patent cohort, whether the patent is subject to renewal fees, and the number of total citations received. In the econometric model, the age dummies capture the life-cyle properties of the trading decision while the time dummies uncover the business cycle effects of the transfer of patents.

The challenge of the estimation strategy is to separetely identify the life cycle and business cycle effects (i.e., age dummies vs time year dummies). We argue that the effects of age and patent categories are identified from the life cycle properties of the trading decision. The probability of a patent being traded is decreasing with age except at the year immediately after a renewal date. The time year dummies, however, are identified by the variation of the characteristics of the patents that are available for trade in any potential time year of transfer and the ones that are actually traded. For instance, consider patents of age 1 and the number of them being traded in a time year conditional on being active. Persistent deviatiations across time from the average of the number of patents being traded for all time years should partly determine the time year dummy. More specificaly, after controlling on patent characteristics, a time year dummy is a weighted average of the persistent deviations in a particular time year for all patents of ages 1, 2, etc.

Another variable we can identify is the patent cohort effects (i.e., the application year dummies). In this case, the identification strategy of the application year dummies is based on variation in the number of years between the application date and the granting date of a patent. One potential problem, however, could be that the "importance" of a patent could be correlated with the lenght of a patent application. A way to deal with the issue when we estimate the probability of a patent being traded is to control by the "importance" of a patent. To operationalize this, we add the total number of citations received by a given year as an explanatory variable.[5]

Table 1 presents the estimates of the time year dummies using alternative econometric models. The first column contains these estimates when age dummies are included. Since the age effects are very important determinant of the trading decision of patents, the time years estimates change significantly. The second column adds the variable that control on whether a patent subject to renewal fees or not. It makes sense to find that the estimates of the time year dummies change. The positive and significant estimate of the dummy variable indicates that patent subject to renewal fees are more likely to be traded than the rest the renewal decision creates sample selection in terms of patent "importance". The third columns adds a dummy variable acknowledging that changes in patent policy during the mid 1980 might have affected characteristics of the stock of patents that are not observable and thus we cannot control. The estimate of the dummy variable is mildly negative, but not statistically significant at standard significance levels. The fourth column introduces patent category dummies to the existing explanatory variables. The dummies are both individually and jointly significant, but the estimates of the time year dummies do not change much. The fifth column adds application year dummies. The dummies are not significant neither individually nor jointly. The level of the estimates of the time year dummies is somewhat lower, but the changes over time, which is what we care about, are not affected. The sixth column adds total citations received by a given year. We find

[5]The total number of citations received by a given age is a common proxy of the "importance" of a patent.

that the effect of total citations is positive and significant at standard significance level, but the estimates of both the time year dummies do not change very much. Finally, the seventh column considers everything except the application year dummies because they are not jointly significant.

4.1 The Relationship Between the Transfer of Patents, GDP and R&D expenditures

The level of the demand for patents and technologies depends on unexpected shocks in technology and the original allocation of property rights among agents. We argue that unexpected shocks in technology make some ideas and patent pools succesful, but for the ideas to be efficiently developed and implemented, some technologies and patents are reallocated to potential buyers with complementary assets and patent portfolios.

In a context of significant reallocation of technology and patents to more productive firms, we should expect that the level of employment, capital and wages should also be affected. Similarly, since property rights are more efficiently allocated and innovation tends to be cummulative, the level of R&D expenditures might increase at the firm level to develop existing innovations and to invest more intensively in new ones because hold up problems have been reduced.

There are a number of patterns that we find:

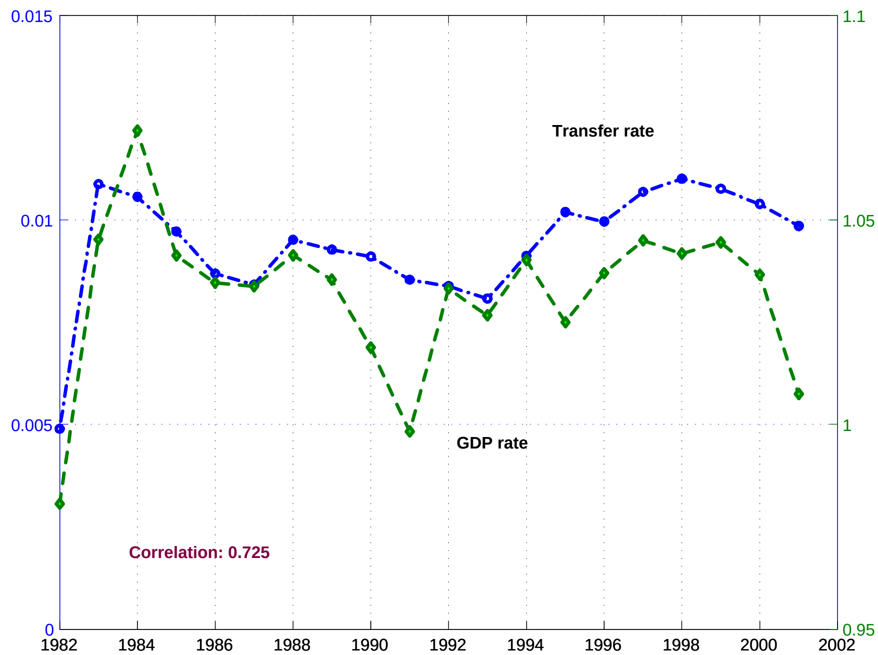
1. *The level of the probability of a patent being traded is positively correlated with the GDP rates.*

Figure 1 plots the predicted probability of the average patent being traded and the rate of growth of GDP from 1982 to 2001.[6] It is interesting to note that the correlation between the predicted probability of transfer and the GDP rates is very high and positive, 0.735.[7]

[6] The prediced probability is constructed using the estimates of the logit model (in columns 7) an evaluating the patent characteristics at the mean of the same of patents in time year 2001.

[7] The correlation between the GDP growth rate and capital fixed investment growth rate between 1982 and 2001 is 0.884.

Figure 1: Probability of a Patent Being Traded and GDP Rate



2. *The level of the probability of a patent being traded is positively correlated with the private R&D expenditure rates.*

Figure 2 presents the predicted probability of a patent being traded and the R&D growth rate from 1982 to 2001. The two series are positively correlated, 0.4028, but less than GDP.

3. *The level of the probability of a patent being traded is positively correlated with TFP rates.*

Figure 3 shows the TFP rates and the probability of a patent being traded from 1982 to 2000. The two series are highly positive correlated, 0.725. The TFP series captures changes in GDP that are not accounted by capital and labor.

The above patterns show that the transfer of patents is a good measure of the sources of the business cycle fluctions. We find that the transfer of patents is positively correlated with GDP, TFP and somewhat less with R&D expenditures.

Figure 2: Probability of a Patent Being Traded and R&D Rate

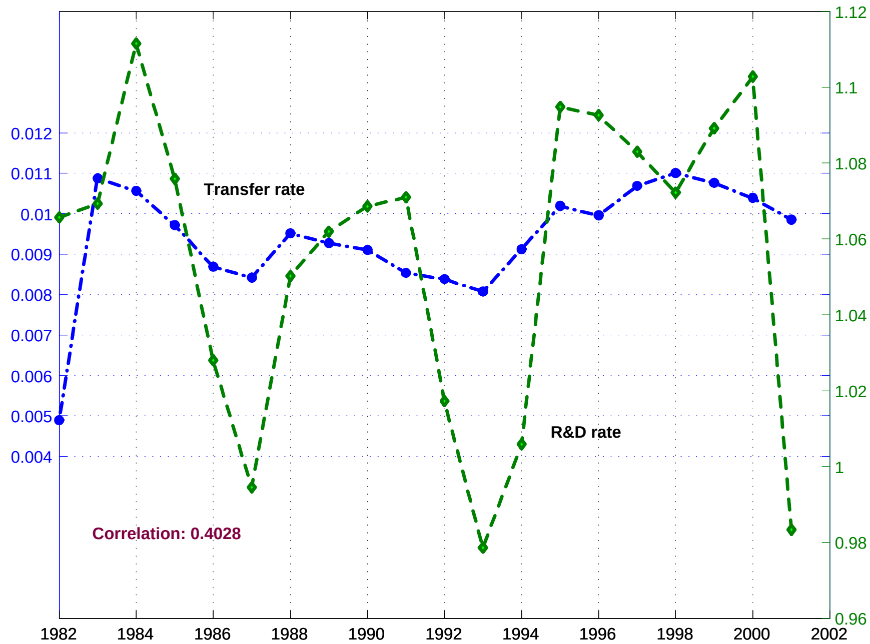
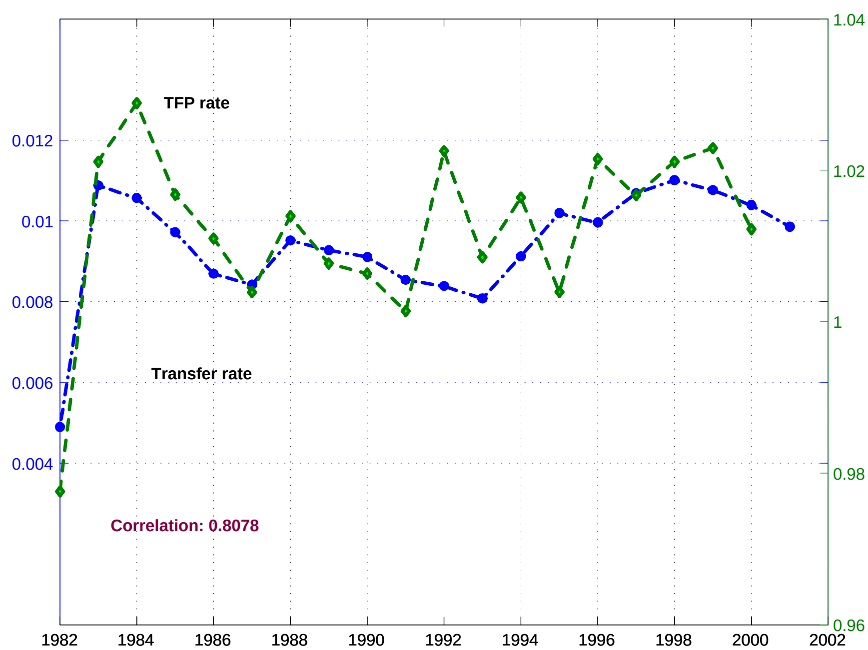


Figure 3: Probability of a Patent Being Traded and TFP Rate



In this context, the sources of the business cycle are related to the reallocation of technological assets, which might also involve the reallocation of labor and capital. We argue that unexpected shocks in technology make some ideas and patent pools succesful. Similarly, given the original firm patent portfolios and their other complementarities assets, unexpected technology shocks make some firms more productive than others in the use of a given patent, but for the ideas to be efficiently developed and implemented, some technologies and patents must the reallocated to new owners.

The reallocation of technology to new owners with a better use should increase TFP. It is interesting to see that TFP, Output and the transfer of patents are highly positive correlated. The patterns suggest that firms adopt fast and efficiently technologies developed by others.

In an attempt to validate the new indicator, it would be interesting to assess the short run fluctuation of the patent grant and the application rate. Figures 4, 5 and 6 in the appendix show its relationship with GDP, TFP and R&D, respectively. The patent grant rate is positively correlated with these variables, but the correlation is much lower than the ones of the transfer rate. Figures 7, 8, 9 in the appendix look at the relationship between the GPD, TFP and R&D with the patent application rate. Similarly, the application rate is positively correlated with GDP and TFP and the correlation is lower than when using the transfer data. On the other hand, the patent application rate is negatively correlated with R&D. These results are consistent with the criticisms made by the previous literature at the use of patent grant and application data for analysis of short run fluctuations. The new indicator, however, has a high positive correlation with the real variables we have used. Moreover, the procyclical properties of the indicator help us learn something about the interplay between the reallocation of technology and business cycle fluctuations.

5 Conclusion

This paper has presented a new direct measure of technological change using data on the transfer of patents. The new patent data addresses two concerns about the use of counts of patents to analyze short run effects of technology shocks. First, while there are long delays between the grant or application of a patent and its commercialization or use, the sale of patents is directly linked to their use in the production and research process through the market of patents. Second, while the economic significance of individual patents or patent counts is very variable, leading to inconclusive inferences between their relationship and output; Traded patents, however, are highly cited and less likely to be allowed to expire.

The new indicator represents the probability of a patent being traded. The measure cannot be directly obtained from the raw data because the probability of a patent being traded does not only depend on business cycle effects, but also depend on the characteristics of a patent and then of the stock of active patents. We use a logit model to separately identify the business cycle from the patent life cycle and characteristics effects. The parameters of the model are identified using variation across and along time in the characteristics of the stock of patents that are active for trade.

Next, we have studied the relationship over time between the new indicator with the GDP rate, TFP rate, and the rate of R&D expenditures. We find that the transfer of patents is highly procyclical and positively correlated with these rates.

We argued that unexpected technology shocks determine what technologies are succesful and the optimal ownership structure of patents. Consequently, given the patent portfolios of firms, the unexpected technology shocks make some firms more productive than others in the use of a given patent. In this way, optimality dictates that patents will be reallocated to better firms, creating improvement gains in the use of technology. The reallocation of patents will have at least two effects. The first one is that the reallocation of ideas to a better use will affect the level of employment, the reallocation of labor, wages and output.

This explains the positive correlation of the new measure with GDP and TFP. The second effect is that the reallocation of technology and intellectual property assets can change the economic incentives of firms to pursue more R&D. Moreover, since innovation is cumulative, the reallocation of patents can carry important economic consequences associated to the long-run prospects of technological change because innovating around them is difficult. This can explain why R&D is positively correlated with the transfer of patents.

The patterns we have presented suggest that unexpected technology shocks might be important as a source business cycle fluctuations. Moreover, the findings open new research questions that could be explored in the future. For instance, firms adopting new technologies should be the ones more likely to represent large changes in TFP, output, R&D expenditures and employment. On the other hand, non adopters of technology and especially firms that transferred patents are more likely to reduce employment, output and exit. To the extent that there are significant cost for workers to reallocate across sectors or firms with different technology, the short run fluctuations in employment could be mixed. Some firms would be hiring workers and the rest -i.e., low value added firms- firing them aggresively. Finally, we hope the new findings will help in the development of new models and determining which ot them are consistent with the data.

6 Appendix

Table 1: Estimates of the Logit Model of the Trading Decision

	1	2	3	4	5	6	7
time_year1983	0.7741 (0.0687)	0.8049 (0.0689)	0.8045 (0.0689)	0.8030 (0.0689)	0.7759 (0.0694)	0.7860 (0.0694)	0.8142 (0.0689)
time_year1984	0.7927 (0.0687)	0.7749 (0.0682)	0.7740 (0.0682)	0.7722 (0.0682)	0.7530 (0.0700)	0.7763 (0.0699)	0.8040 (0.0682)
time_year1985	0.7788 (0.0669)	0.6885 (0.0682)	0.6874 (0.0682)	0.6875 (0.0682)	0.6585 (0.0767)	0.6944 (0.0715)	0.7349 (0.0682)
time_year1986	0.7023 (0.0667)	0.5753 (0.0686)	0.5739 (0.0687)	0.5744 (0.0687)	0.5312 (0.0740)	0.5767 (0.0741)	0.6321 (0.0687)
time_year1987	0.6862 (0.0662)	0.5434 (0.0686)	0.5416 (0.0687)	0.5413 (0.0687)	0.4896 (0.0767)	0.5413 (0.0767)	0.6060 (0.0688)
time_year1988	0.8388 (0.0646)	0.6675 (0.0676)	0.6636 (0.0679)	0.6606 (0.0679)	0.6019 (0.0790)	0.6583 (0.0791)	0.7310 (0.0680)
time_year1989	0.8083 (0.0644)	0.6422 (0.0678)	0.6354 (0.0686)	0.6285 (0.0686)	0.5601 (0.0830)	0.6191 (0.0831)	0.7033 (0.0687)
time_year1990	0.8168 (0.0638)	0.6255 (0.0678)	0.6161 (0.0693)	0.6051 (0.0693)	0.5238 (0.0872)	0.5837 (0.0873)	0.6825 (0.0694)
time_year1991	0.7412 (0.0639)	0.5610 (0.0682)	0.5499 (0.0703)	0.5367 (0.0703)	0.4541 (0.0921)	0.5134 (0.0922)	0.6156 (0.0704)
time_year1992	0.7124 (0.0638)	0.5448 (0.0684)	0.5323 (0.0710)	0.5161 (0.0710)	0.4253 (0.0971)	0.4827 (0.0972)	0.5953 (0.0712)
time_year1993	0.7157 (0.0639)	0.5095 (0.0688)	0.4959 (0.0719)	0.4760 (0.0719)	0.3758 (0.1026)	0.4310 (0.1026)	0.5554 (0.0720)
time_year1994	0.8705 (0.0633)	0.6344 (0.0685)	0.6199 (0.0720)	0.5969 (0.0720)	0.4908 (0.1078)	0.5420 (0.1078)	0.6759 (0.0721)
time_year1995	1.0251 (0.0627)	0.7481 (0.0681)	0.7328 (0.0721)	0.7070 (0.0721)	0.6026 (0.1132)	0.6476 (0.1132)	0.7841 (0.0722)
time_year1996	1.0510 (0.0627)	0.7278 (0.0684)	0.7118 (0.0728)	0.6821 (0.0728)	0.5889 (0.1191)	0.6267 (0.1191)	0.7573 (0.0729)
time_year1997	1.1610 (0.0625)	0.8010 (0.0682)	0.7844 (0.0729)	0.7521 (0.0729)	0.6743 (0.1249)	0.7030 (0.1249)	0.8244 (0.0729)
time_year1998	1.2437 (0.0624)	0.8340 (0.0682)	0.8170 (0.0731)	0.7815 (0.0731)	0.7164 (0.1308)	0.7339 (0.1308)	0.8493 (0.0732)
time_year1999	1.3155 (0.0622)	0.8139 (0.0681)	0.7966 (0.0731)	0.7576 (0.0731)	0.7015 (0.1366)	0.7055 (0.1366)	0.8201 (0.0732)
time_year2000	1.3294 (0.0621)	0.7799 (0.0680)	0.7623 (0.0732)	0.7219 (0.0732)	0.6762 (0.1424)	0.6663 (0.1424)	0.7782 (0.0733)
time_year2001	1.2768 (0.0622)	0.7269 (0.0681)	0.7091 (0.0735)	0.6677 (0.0735)	0.6356 (0.1481)	0.6128 (0.1481)	0.7180 (0.0735)

Dummies							
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No subject to renewal fees	No	Yes	Yes	Yes	Yes	Yes	Yes
Patent policy	No	No	Yes	Yes	Yes	Yes	Yes
Patent Category	No	No	No	Yes	Yes	Yes	Yes
Application year	No	No	No	No	Yes	Yes	No
Total citations received	No	No	No	No	No	Yes	Yes

Significant at 1%, or * 5%, ** or 10%, and *** means not significant at 10%

Figure 4: The Patent Grant Rate and the GDP Rate

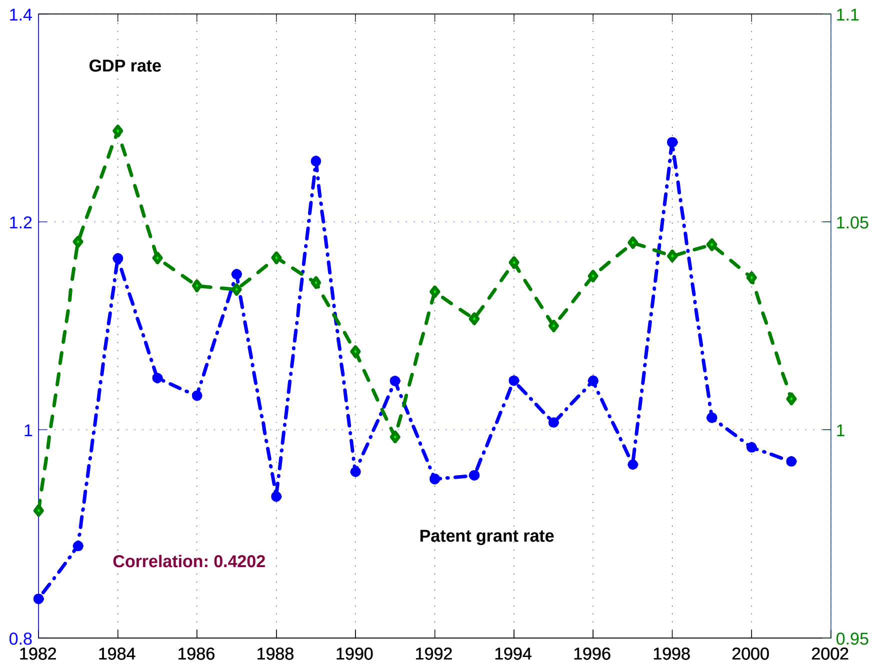


Figure 5: The Patent Grant Rate and the R&D Rate

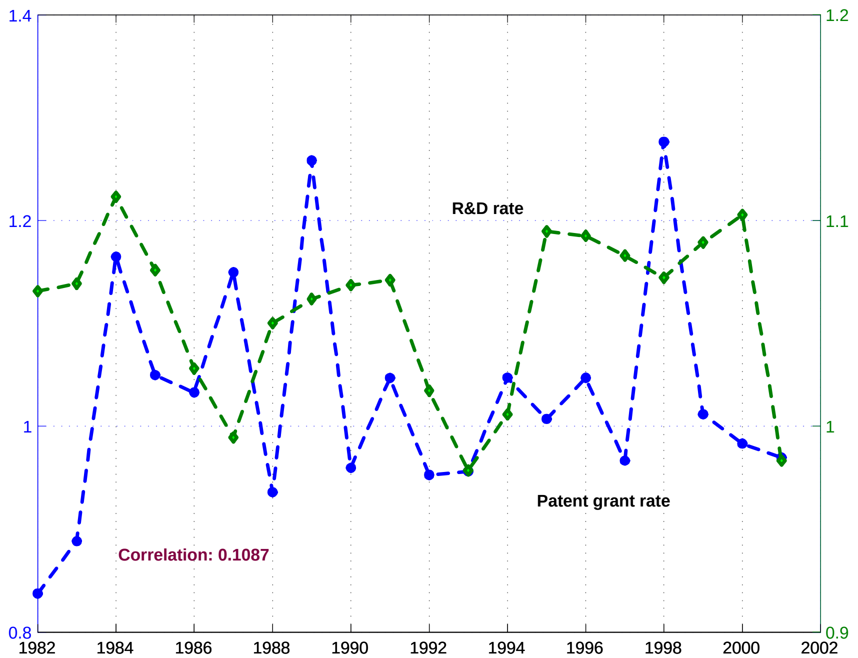


Figure 6: The Patent Grant Rate and the TFP Rate

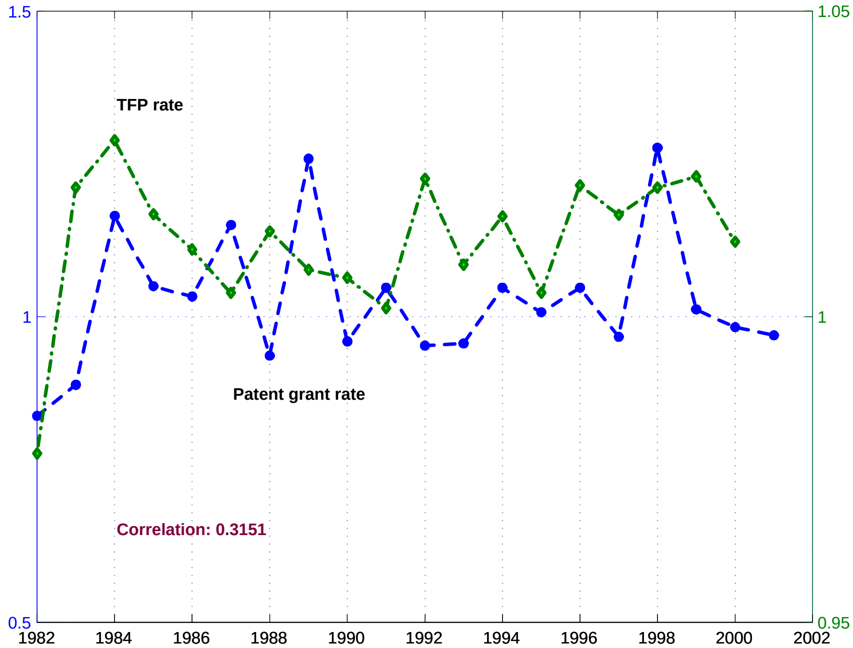


Figure 7: The Patent Application Rate and the GDP Rate

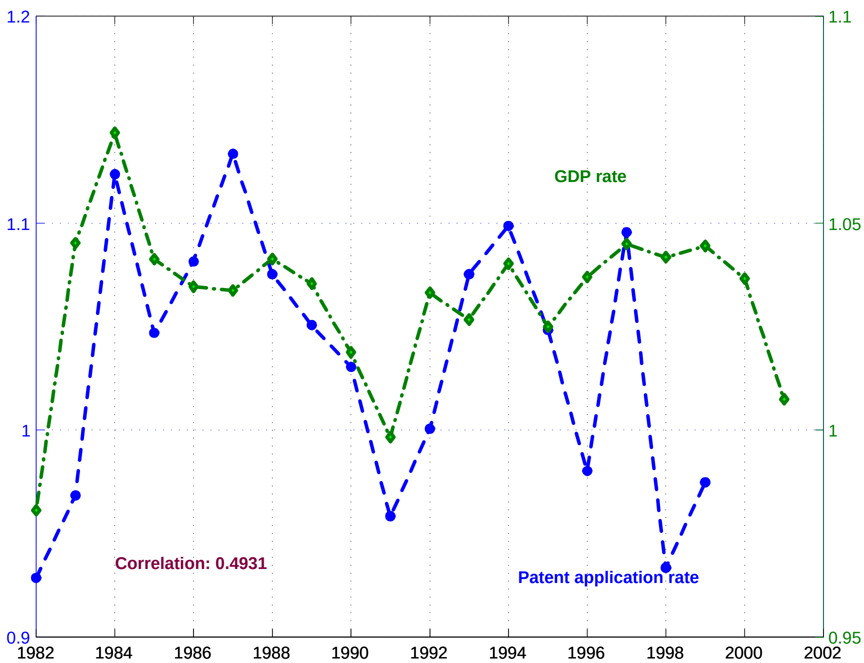


Figure 8: The Patent Application Rate and the R&D Rate

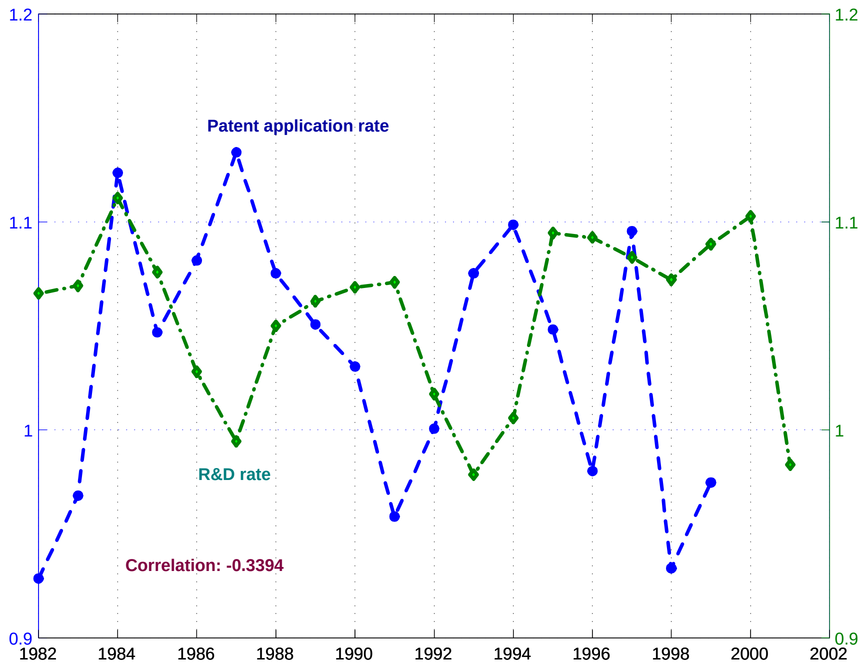
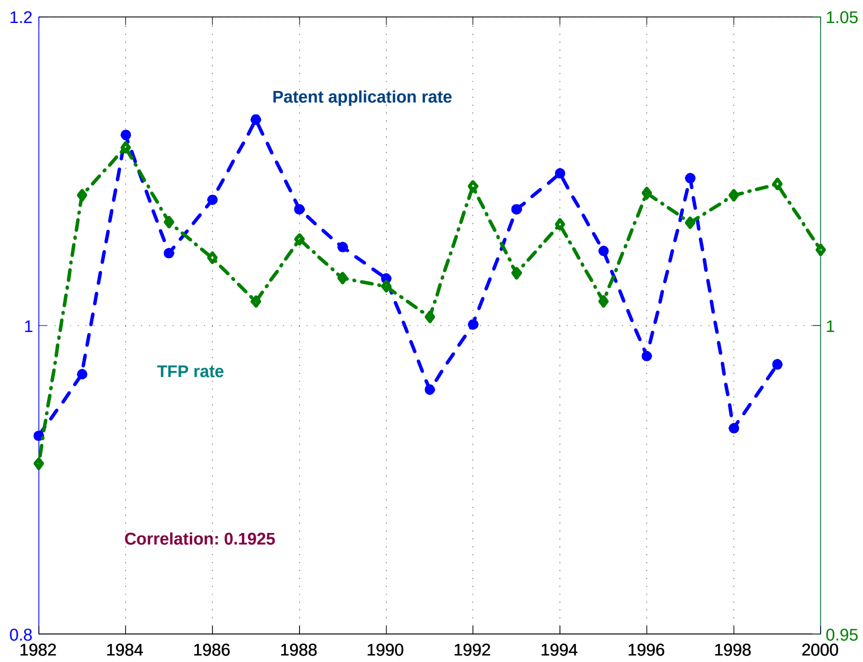


Figure 9: The Patent Application Rate and the TFP Rate



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