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Valuing Patents on Market Reaction to Patent Infringement Litigations

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***Abstract*—**Innovation is more important in any companies. However, it is not easy to measure the innovation performance correctly. Patent is one of measuring index nowadays. This paper wants to purpose an approach for valuing patents based on market reaction to patent infringement litigations. The interesting phenomenon is found from collection of patent infringement litigation events. That is if any patent litigation event occurs the stock value will follow changing. The plaintiffs' stock value raises some percentage. According to this interesting phenomenon, the relationship between patent litigation and stock value is tested and verified. And then, the stock value variation is used to deduce the infringed patents' value. The purpose of this study is providing another concept model to evaluate the infringed patents. This study can provide a decision assist system to help drafting patent litigation strategy and determine the technology value.

***Keywords*—**Patent valuation, infringement litigations, stock value, artificial neural networks.

I. Introduction

As the knowledge economics grows rapidly, the value of intangible assets is more emphasized in business field nowadays. Intangible assets include intellectual capital and intellectual property. Intellectual Property Rights (IPRs) can be highly valuable rights playing a critical role in many fields of business [1]. In addition, there is a growing awareness that the success of many companies is dependent on technological innovation and one way of analyzing a company's ability to innovate is through evaluation of its patent portfolio [2]. Patent can protect the latest ideas of companies and be represented the competitiveness' R&D results. If companies do not keep up with the latest ideas to patenting, they may be left behind by competitors developing more advanced and marketable products. This is especially true in hi-tech industries [2]. For this reason, many companies try to defend their patent rights by patent litigation. The case of patent litigation grows doubled every year in the past decade. Patent litigation becomes the most important strategy in business war. So far, the study of patent litigation has been based mostly in the economic literature, with its primary focus being public policy questions about patents and innovation in the economy [3].

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The litigation of Intellectual Property Right influences enterprise deeply, and it maybe reshuffle the business domain. For example, Microsoft has reconciliation in the antitrust case and then it's stock value rise 7% on that day. This again is demonstrated by real-world events. When a Japanese trial court ruled in August 1994 against TI's claim that Fujitsu had infringed the Kilby patent, TI's stock price fell by 5.6%, a loss in market capitalization of some US$ 426.5 million [4, 5]. The stock of Rambus, a designer of high-speed memory chips, fell some 54% (a loss in market capitalization of over US$ 1.9 billion) over a 2-day period in March 2001 in response to news that a judge over-seeing a patent infringement case brought by Rambus intended to interpret the claims in some of Rambus' patent in a narrow fashion [5, 6]. And in September 2004, Nikon and ASML, two producers of lithography systems used by firms such as Intel to produce computer chips, settled several patent litigation procedures. Nikon and ASML accused each other of infringing the other's patents with respect to several different aspects of their systems. The settlement called for ASML (and its main supplier) to pay Nikon a total of €119 million [7]. Many cases have been cited in [8] as landmark developments in the IT industry as far as patent litigations are concerned. This includes the almost US$1 billion award in favor of Polaroid in the Polaroid vs. Kodak dispute, which put Kodak out of the instant photo business, and Texas Instruments taking legal actions on nine Asian companies for infringing on its DRAM (Dynamic Random Access Memory) patents. A rich set of literature on litigations [9, 10] has argued for an examination of market-based approaches to studying economic impact of litigations. Since empirical evidences show the influences of patent infringement litigations are obvious, it is important to understand relationship between patent litigation and firm stock value.

By collecting preliminary data and literatures, patent litigations and firm stock values are remarkable related. The database of patent litigation cases and the corresponding firm's stock value data are built up and the stock value variation model is established by using this database. The value of infringed patents can be gained by mapping the stock value variation model. The patents with litigated are at least a subset of the most valuable patents and so the easiest way to learn about the characteristics of valuable patents is therefore to study litigated patents [11]. According to the researches of [11] and [12], those characteristics of litigated patents are adopted as our input data in the model and the output data is stock value variation of litigated companies. Artificial neural networks method is used to build the forecast model. This study can provide a decision

assist system to help drafting patent litigation strategy and determine the technology value.

This paper is organized as follows. The related literatures are reviewed in the Section 2. The model construction and implementation are showed in Section 3. In Section 4 is illustrative case. Finally, conclusions are presented in Section 5.

II. The Relationship between Patents, Patent Litigation and the Market Value

Numerous articles show that IPRs in particular are increasingly important. The value of firms in knowledge intensive activities is determined by the value of its IP. The recent literature on the impact of IP on the value of the firm, its assessment, valuation, accounting and management of IP are reviewed in [13]. The detailed of intellectual property rights management practices are understood by Hanel's study. The articles about the patents, patent litigation, and the market value with patents or litigations are reviewed in this study.

Reference [14] first discussed the relationship between stock performance and patents. References [9] and [10] have argued for an examination of market-based approaches to studying economic impact of litigations. Patent owner's behaviors in patent litigation events were discussed in [15]. The cost of patent prosecution as the indicator to evaluate patents was used in [16]. The behaviors in patent prosecution [17] and in patent infringement lawsuits for evaluating patents [18] were discussed.

An extensive summary of event studies applied to issues of litigations and corporate law is presented to demonstrate its usefulness in assessing the impact of corporate policy on shareholder wealth creation [19]. Event study in patent litigation context enables us to study patent impact in the context of a rival firm that may also benefit from the innovation and investigate the influence of both firm specific and patent specific variables. Event studies have also been used in litigations as evidence for damages and liabilities. Litigations have a big impact on indirect costs such as management distraction and difficulty in obtaining credit on favorable terms. Such high indirect costs cause market to reevaluate the litigating firms' market valuation.

A favorable stock-price influence when the number of patents, the scientific merit of patents, and the R&D spending were high, where patent citation information could indeed help investors judge the future profit-earning potential of a firm's scientific discoveries [20]. Reference [21] concluded that actions of the prosecution were positive to the market value of the patent owner and the patent infringement lawsuit affected the firm's strategies [22].

Capital market reactions to litigation announcements were as a measure of the economic impact of patent litigations in [23]. The contribution of their study were two fold: First, using a market based approach; it examines the economic significance of patent litigations in the IT industry to the firms involved and demonstrates the market's bias towards patent holders in litigations. Second, it investigates factors that could affect the market's reactions to patent infringement litigations in the IT industry and explores the possibility of systematic differences in the market's reactions based on a number of covariates related to the litigation. The empirical evidence shows that the market's reaction is clearly slanted to the holder of the patent rights.

Patent litigation incident on the stock price has a significant relationship according to the above literatures. Though these literatures discussed patents and indicators in view of patent law, there is no corresponding valuation model built yet. The principle valuation method are: (1) Industry standards (key is finding an appropriate benchmark); (2) Rules of thumb (25% rule and many variants thereof); (3) Rating-Ranking; (4) Discounted cash flow; (5) Advanced methods (Monte Carlo, Real options pricing); (6) Auctions [13]. Reference [24] proposed an objective scoring system for patents from the licensor side using the Analytic Hierarchy Process to value patents for new products being developed by an actual enterprise. The purpose of this study is providing another concept model to evaluate the infringed patents. The stock value variation is used to deduce the infringed patents' value. The methodology is as follows.

III. Methodology

In this research, the stock value variation is used to deduce the infringed patents' value. There are two stages to reach the purpose. First, the stock value variation forecasting model needs to establish by artificial neural networks. Secondly, the infringed patents' value (IPV) can be calculated that individual stock price multiplied by its' variation and multiplied by common stock outstanding in the period of litigation.

A short overview of the artificial neural networks (ANNs) and the backpropagation training algorithm are introduced in this Section. ANN-approaches are a very attractive tool for the management scientist and can be used to solve a number of different problems on a quite sophisticated level. In this way ANN-methods could be used appropriately to corroborate previously conjectured theory on the one hand but also, on the other hand, as a data-driven explorative research instrument detecting structural information not considered before [31]. According to the advantage of ANN-methods, ANN is adopted in this research.

The detail about artificial neural networks may refer to [25] and [26] for an introduction to ANN, and refer to [27]-[29] for a more detailed description of ANN learning algorithms and topologies.

An ANN consists of a number of connected nodes, each of which is capable of responding to input signals with an output signal in a predefined way. These nodes are ordered in layers. A network consists of one input layer, one output layer, and an arbitrary number of hidden layers in between. This number can be chosen by the user such that the network performs as desired. One or two hidden layers are popularly used. One reason for this is that one hidden layer is sufficient to approximate any continuous function to an arbitrary precision [30](Hornik et al., 1989).

The ANN consists of three layers, the input layer, one hidden layer, and the output layer. The nodes are connected such that each node is connected to all nodes of the previous and the successive layer if such layers exist. The input layer is only connected forward to the first hidden layer and the output layer only backward to the last hidden layer. All connections are assigned a weight a real number. An ANN also contains biases. These are dummy nodes which always provide an output of +1. They are useful in translating the [0, 1] output from the logistic function.

Similar to estimation of logit model over estimation period data, the ANN gets trained on a set of training data. ANN starts out by an initial set of weights chosen randomly, typically between (-1, 1). It then adapts the weights in such a way that given the input signals, the ANN's output signal(s) match the desired output signal(s) as closely as possible.

A popular algorithm called the backpropagation algorithm is used in this study. The basic algorithm works as follows. The input to a node is computed as the sum of the outputs of the preceding nodes multiplied by the weight of the connection. This is expressed as

$$NET = \sum_{i=1}^{n} OUT_i w_i \tag{1}$$

where

OUT_i = the output of node *i* in the previous layer,

w_i = the corresponding connection weight.

For the input layer OUT_i is simply the vector of input values. This sum is then transformed to a value between 0 and 1 using the so called logistic or sigmoid function.

$$OUT = \frac{1}{(1+e^{-NET})} \tag{2}$$

Starting with the first hidden layer, this calculation is done from left to right until the output layer is reached. All training pairs are presented to the ANN and the sum of squared errors when the whole training set is computed. If the sum of squared error exceeds the specified error tolerance, the ANN adjusts the connection weights— this is called a training epoch. The ANN then begins training epoch until either the maximum number of training epochs is reached or the sum of squared errors reaches the specified error tolerance. The training is completed when either of this happens. One can think of this as moving on the error surface in the direction of the steepest descent. How well a network is trained is measured by the mean sum-squared error over the complete training dataset.

The connection weights are adjusted as follows. Starting with the weights connecting output layer and the hidden layer the weight adjustments are propagated backwards using

$$\delta_{p,output} = OUT(1-OUT)(TARGET - OUT) \tag{3}$$

where $\delta_{p,output}$ is the delta value of node *p* in the output layer. Based on this the weight change is calculated:

$$\Delta w_{pq,k} = \eta \delta_{qk} OUT_{pj} \tag{4}$$

where

$\Delta w_{pq,k}$ = weight change of connection from node p in layer *k*-1 to node *q* in layer *k*,

η = learning rate (which can be set by the user),

δ_{qk} = delta value for the node *q* in layer *k*, and

OUT_{pj} = output of node *p* in layer *j* (same as *k*-1).

The new weight assigned to this connection is computed as

$$w_{pq,k}(n+1) = W_{pq,k}(n) + \Delta w_{pq,k} \tag{5}$$

where n denotes the current iteration (before weight adjustment) and *n*+1 the next iteration (after weight adjustment). This procedure is repeated for all nodes in the output layer. Afterwards the incoming connections of the previous layer are updated.

For layers except the output layer is computed as followed:

$$\delta_{p,j} = OUT_{p,j}(1-OUT_{p,j})(\sum_{q} \delta_{q,k} w_{pq,k}) \tag{6}$$

where

$\delta_{p,j}$ = delta value of node *p* in layer *j*,

$OUT_{p,j}$ = output of node *p* in layer *j*,

$\delta_{q,k}$ = delta value for the node *q* in layer *k*, and

$w_{pq,k}$ = weight of connection from node *p* in layer *k*-1 (same as *j*) to node *q* in layer *k*.

The following steps remain the same. This procedure continues until a small error is reached or a specified number of training epochs are over.

Backpropagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and non-linearly differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associated input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by us. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Standard backpropagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks.

Back-propagation is the most commonly used training algorithm for neural networks. The weights are updated as follows

$$\Delta w_{ij}(t) = -\eta \frac{\partial E(t)}{\partial w_{ij}(t)} + \alpha \Delta w_{ij}(t-1) \tag{7}$$

where η is the learning rate, and α is the momentum.

The learning rate, η, controls the rate at which the network learns. Usually, the higher the learning rate, the faster the network learns. The valid range is between 0.0 and 100.0. A good guess is 0.1 when training a new network at the beginning. If the learning rate is too high the network may become unstable, at which time the weights should be randomized and training restarted.

The momentum parameter, α, controls the influence of the last weight change on the currently updated weight. The valid

range is 0.0 to 1.0. Momentum usually results in faster learning, but can cause instability in some cases if set too large.

Backpropagation can train multilayer feed-forward networks with differentiable transfer functions to perform function approximation, pattern association, and pattern classification. Other types of networks can be trained as well, although the multilayer network is most commonly used. The backpropagation refers to the process by which derivatives of network error, with respect to network weights and biases, can be computed. This process can be used with a number of different optimization strategies. The architecture of a multilayer network is not completely constrained by the problem to be solved. The number of inputs to the network is constrained by the problem, and the number of neurons in the output layer is constrained by the number of outputs required by the problem. However, the number of layers between network inputs and the outputs: the size of the layers is up to the designer. The two-layer sigmoid/linear network can represent any functional relationship between inputs and outputs if the sigmoid layer has enough neurons. There are several different backpropagation training algorithms. They have a variety of different computation and storage requirements, and no one algorithm is suited to all cases.

Training neural networks may cause the network overfit on the training set and not generalize well to new data outside the training set. This can be prevented by training with trainbr, but it can also be prevented by using early stopping with any of the other training routines. This requires that the user pass a validation set to the training algorithm— in addition to the standard training set. To produce the most efficient training, it is often helpful to preprocess the data before training. It is also helpful to analyze the network response after training is completed.

IV. Illustrative Case

A. Data and Sample

The study focuses on both groups of firms involved in patent infringement litigation. They are the firms that are claiming the infringement damages (named as the plaintiffs) and the target firms of litigations (named as the defendants).

This study focuses on the patent infringement lawsuits in U.S. district courts of Delaware, California and Texas. Those lawsuits having final judgment exterminations and indicating definite patent numbers and damage awards are regarded as the effective samples. In this study, the LexisNexis database is used to collect and filter patent litigation cases. The selected volume of patent litigation cases are 65 cases, among 37 cases of Delaware, 24 cases of California and 4 cases of Texas. And a total number of patents are contains a total of 163. The use of stock returns as a metric for litigation impact requires that both plaintiff and defendant firms be publicly traded. This narrows the sample of firms that are studied but prevents the possibility of returns being skewed by a preponderance of non-publicly traded firms among either type of litigants. And the impact on the stock returns are measured around the day of the commencement of litigation and subsequently the day the litigation is settled or a judgment is made.

Therefore, there are 13 samples on the commencement of litigation and 15 samples on the settlements from the plaintiffs. There are 11 samples on the commencement of litigation and 14 samples on the settlements of litigation from the defendants. In sum, there are 24 samples on the commencement of litigation and there are 29 samples on the settlements of litigation. The two groups' samples are as input data in ANN model.

According to the results of [23], the effect of the litigation on the stock market returns around the date of litigation announcements as well as the date of settlement. And the stock value variation data is during the announcement or settlements period [denoted as (-1, +1)-day -1, the preceding day and day +1, the day after announcement or settlements.

B. Delimitation and Limitation

There are some delimitations and limitations in this research. They are as follows.

1) There are several categories of U.S. patents, such as utility, design, plant, defensive publication, statutory invention registration, and additional improvement, etc. The compositions of all these categories differ from each other. This study discusses the utility patent only.
2) There is at least one patent included in a patent portfolio which is enforced in a patent infringement lawsuit to win a lump sum of the damage award. Only damage award of the portfolio is discussed.
3) Only patent infringement lawsuits with final judgment of determination are analyzed. Settled lawsuits should be excluded from effective samples.
4) Patent infringement lawsuits are retrieved from three district courts which are famous in huge quantity and fast judgment of patent infringement lawsuits, i.e. district court of Delaware, district court of California, and district court of Texas.
5) Patent infringement lawsuits are retrieved in the period of 1944 to 2006 in both district courts of Delaware and California. But because district court of Texas is famous in showing favor to plaintiffs, lots of lawsuits get settlements, few lawsuits with final judgment of determination are found. Hence, patent infringement lawsuits of district court of Texas are retrieved from 1994 to 2006.

C. Definition of Patent Indicators

By reviewing previous literatures, [12] propose the integrated indicators of patent. Therefore, the integrated indicators are adopted in this study. The 17 quantitative patent indicators are from X_1 to X_{17}, finally summarized for describing the features of a patent as shown in Table I [12].

TABLE I
THE DEFINITION OF PATENT INDICATORS

Variable	Name	Definition
X_1	Assignees	the assignee count of each patent
X_2	Inventors	the inventor count of each patent
X_3	Total claims	the total claim count of each patent
X_4	Independent claims	the independent claim count of each patent
X_5	US patent references	the count of US patent documents listed in the field of "References Cited", i.e. prior arts recognized by the examiner, of each patent. In some literatures, "US patent references" is usually called "Backward citation"
X_6	Foreign patent references	the count of foreign patent documents in the field of "References Cited" of each patent
X_7	Non-patent references	the count of other publications (non-patent literatures, including papers, handbooks and magazines, etc.) in the field of "References Cited" of each patent. In some literatures, "Non-patent references" is usually called "Science linkage"
X_8	Forward citations	the count of follow-up citing patents by the other patents by the date of the beginning of lawsuit of each patent
X_9	International Patent Classifications (IPC)	the count of IPCs which recognized by the examiner of each patent
X_{10}	US Patent Classifications	the count of USPCs which recognized by the examiner of each patent
X_{11}	Worldwide patent family	the count of worldwide related patents those claimed at least one same priority of each patent. This count is investigated based on INPADOC database
X_{12}	US patent family	the count of US related patents those claimed at least one same priority of each patent. This count is investigated based on INPADOC database
X_{13}	Office actions	the count of office opinions by the examiner of USPTO of each patent. The office opinions include the selection by restriction, non-final rejection, final rejection, and notice of allowance, etc
X_{14}	Responses	the count of responses to USPTO by the assignee of each patent. The responses include amendments, response to non-final rejection, response to final rejection, request for continued examination, and appear, etc
X_{15}	Examination	the time span from filing date to issue date of each patent
X_{16}	Drawing	the count of drawings of each patent
X_{17}	Life-span	the time span from filing date to the beginning of lawsuit of each patent

D. Constructing Neural Network Model to stock value variation

The neural network is used to build up the forecasting model of stock value variation. The input variables for the proposed neural network in this study are 17 factors and the output variable is the stock value variation. For constructing the neural network, at least two sets of samples are necessary, i.e. a training set and a testing set, for iteratively tuning the NN by training and testing. Design of the standard feed-forward backpropagation neural network after adjustment with the software tool "NeuroSolutions". The performance of model is evaluated by Mean Squared Error (MSE). When the value of MSE is small, it means that the model's error is small. The formula of MSE is below.

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{N \cdot P} \quad (8)$$

where

P : is the output of node ;

N : is sample size ;

d_{ij} : is the real value in the *j* node;

y_{ij} : is the output value in the *j* node.

The stock value variation (SVV) is be calculated by the following formula.

$$SVV = \left|(V_{t+1} - V_{t-1)} / V_{t-1}\right| \quad (9)$$

Where

V_{t+1} : is the stock value after the events' day;

V_{t-1} : is the stock value before the events' day.

Finally, the infringed patents' value (IPV) can be calculated by the formula as follows.

IPV= Stock price * SVV* common stock outstanding in the period of litigation. (10)

E. Results and discussion

By the neural network training tests, the three have been a better model for studying the effect of litigation on the date the samples, from 50 percent the proportion of test samples, number of iterations 5000 times, 10000 times, 50000 times the model, the test error value can be reduced to around 0.025. Therefore, this study within the commencement of litigation samples can have a good prediction of the effect of stock value variation.

After the training procedure, one can find the best model is that the training sample is 50%, and the iteration is 5000, 10000 and 50000. The results are in the Table II. And Fig. 1 shows the compared the real output value and forecasting output value in 50000-iteration model.

TABLE II
THE RESULTS FROM TRAINING PROCEDURE

The ratio of samples	Iterations	Frequency	MSE of training	MSE of testing
50%	5000	1	0.0002543	0.0250683
		2	0.0002455	0.0245315
		3	0.0002594	0.0273184
		mean	0.0002531	0.0256394
	10000	1	0.0002234	0.0249569
		2	0.0002228	0.0254037
		3	0.0002239	0.0248272
		mean	0.0002233	0.0250626
	50000	1	0.0002216	0.0258208

The ratio of samples	Iterations	Frequency	MSE of training	MSE of testing
		2	0.0002209	0.0249800
		3	0.0002215	0.0243603
		mean	0.0002214	0.0250537

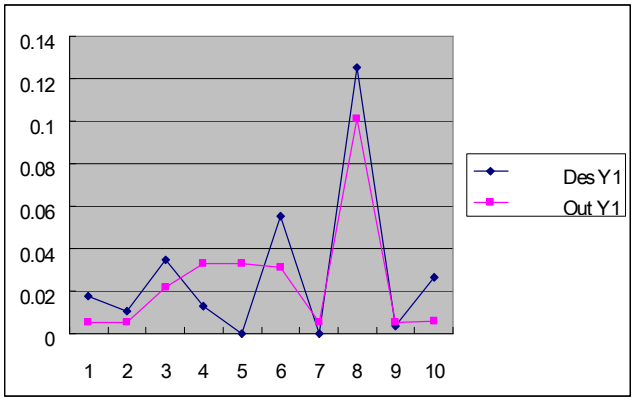

Fig. 1 The compared the real output value and forecasting output value in 50000-iteration model

And the data of 29 samples on the settlements of litigation did not have a good predictive capability and the testing MSE error values are too large. So as to find possible reasons for this result is that stock markets will not be affected when the patent litigation is settlement. It may be the patent litigation decides judicially is not so significant for investors or said that the investment people gradually forget the matter. So in order to patent litigation in the proceedings scheduled to decide judicially day and date on the company's stock price impact, the patent litigation cases in proceedings on the day of the company's share price will be significantly affected, but also from the proceedings to date to predict changes in stock prices, and decide judicially determined to date company's share price changes in the relative degree of impact on the obvious, more difficult to decide judicially date set to predict price changes.

V. Conclusions

Increasing the number of cases of patent litigations in recent years, the awareness of intellectual property protection for the technology industry is growing. Many companies fight patent litigation to defend their rights and it has become a race competition and one important strategy when a business with others.

By collecting preliminary data and literatures, patent litigations and firm stock values are remarkable related. The database of patent litigation cases and the corresponding firm's stock value data are built up and the stock value variation model is established by using this database. The value of infringed patents can be gained by mapping the stock value variation model. The patents with litigated are at least a subset of the most valuable patents and so the easiest way to learn about the characteristics of valuable patents is therefore to study litigated patents [11]. According to the researches of [11] and [12], those characteristics of litigated patents are adopted as our input data in the model and the output data is stock value variation of litigated companies. Artificial neural networks method is used to build the forecast model and the forecasting results are good. The ANN method is good for build up the model.

In this study, ready to provide the company's future patent litigation or patent litigation happen, we can grasp the impact of events on share price, from a good neural network model for prediction of changes in company's share price may help the company patent litigation strategy and response mechanisms for the formulation. The results of this study provide a novel model to calculate infringed patents value. It can provide a decision assist system to help drafting patent litigation strategy and determine the technology value.

Whether the plaintiff or the defendant company, must pay close attention to patent litigation will affect prime time, especially in the power of the strongest the first 2 days and 1 days, all the strategy and response mechanism must be controlled within 5 days inside to be able to achieve the desired effect. Otherwise, they will miss the market response time, for example: the plaintiff will likely miss the market value of upgrading to take advantage of market opportunities for the reaction, and the defendant may be missed to reduce the irreversible loss of market timing.

In this study, through the relevant literature and research methods to confirm patent litigation, patent value, shares of the relationship between the three, so will assess the value of patents as a model of factors independent variables and changes in stock price as a contingency item, so this study was to patent indicators can be used to predict the value of patent litigation incident on the impact of stock prices, in other words, declared the impact of patent litigation is precluded by time changes in stock prices caused by changes in market value, be inferred that this change is to represent the value of patent litigation in this case the value of patents .

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