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Abstract

This paper adds to the literature on the Sarbanes-Oxley Act's net effects by looking at whether its passage was associated with a change in innovation and patenting. Its effects are separated into temporary uncertainty and changes in long term investment incentives in a dynamic programming problem faced by innovators who learn over time about SOX's effect. Innovation is found to fall under uncertainty for potential losses that are low relative to the potential profits. As companies learn, innovation rates readjust to SOX's long term persistent effect. We examine US patenting in stem cell technologies from 2001 to 2009 for SOX related changes. To reduce the dependence of our estimates on timing assumptions, we look for changes over the whole period. We firstly use a rolling break test with a single break point with Monte Carlo correction to p-values for search process endogeneity and MLE bias. Secondly, we run a hidden Markov model allowing for multiple states in the patent process and transitions between the states. We find a large and statistically significant change at a date consistent with a SOX effect under both testing methods. A three state hidden Markov model finds subsequent correction consistent with the theoretical model. Four competing explanations are found to account incompletely for the observed data.

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1 Introduction

The US Sarbanes-Oxley Act (Sarbanes-Oxley, 2002, hereafter SOX) was a regulatory response to financial scandals in the early 2000s. It imposed new disclosure requirements on companies, placed increased restrictions on the behaviour and conflicts of interests for company insiders, and specified new penalties for related malfeasance. Auditors and securities analysts were also subject to more stringent regulations on their behaviour, and a new not-for-profit company, the Public Company Accounting Oversight Board (PCAOB), was established to oversee auditors and audit quality.

Many regulatory demands of SOX could incur costs for companies. The PCAOB, for instance, is funded by company levies, and the increased demands on auditor quality could be passed on as greater charges for audit. The net effect of SOX on available company funds is not apparent as the Act may increase investor confidence in investment at the same time as increasing the effective charges levied against that investment. Neither is it clear what the change will be in incentives for particular managerial uses of the available funds. For example, activities that are more heavily regulated in the new rules may be relatively less profitable relative to other activities after SOX.

Given these uncertain effects on company funding and incentives, the literature has examined the association between the passage of SOX and contemporaneous changes in a variety of financial and non-financial corporate variables. They include market return (Li *et al.*, 2008; Zhang, 2007), equity cost (Ashbaugh-Skaife *et al.*, 2009), investment discount factors (Kang *et al.*, 2010), cross-listing premium (Litvak, 2007), company cost and structure (Linck *et al.*, 2009), market entry choices (Engel *et al.*, 2007; Leuz *et al.*, 2008), and research and development spending (Bargeron *et al.*, 2010).

This paper examines whether SOX was associated with a change in technological innovation by affected companies. SOX may have altered their available funding for research and development or managerial preferences for such risky activities as found by Bargeron *et al.* (2010). Innovation represents an investment in intellectual property made in anticipation of a stream of future income from its commercialisation, and the decision to invest depends on revenues net of SOX's effects.

We formulate the dynamic problem faced by a company considering an irreversible investment in innovation. Future income is uncertain and subject to an additional uncertainty linked to SOX. As time passes, investment behaviour changes endogenously as companies learn about SOX's effect. Kang *et al.* (2010) present an investment model in which managers maximise utility from future income, but contrary to our formulation managerial preferences are adjusted exogenously in response to SOX. Bloom (2009) and Guo *et al.* (2005) describe models with variable uncertainty able to generate endogenous dynamics in investment behaviour similar to ours. They differ in their assumption of less than complete investment irreversibility, their transition process for uncertainty, and their use of simulation.

Our problem's solution indicates that delays in investment occur if the potential losses through early ignorant investment are even moderately sized relative to the potential gains, if learning is quite rapid, and if discounting of future income is not very large. We present evidence that these conditions apply after SOX's passage. The transient, and generally patent reducing, effect of uncertainty is distinguished from SOX's long term effects which are ambiguous.

We test for the existence of a change in company innovation after SOX by examining the time series of patent rates in stem cell technologies. The stem cell technology industry is new, small, and risky. These characteristics have often been found to be linked to magnification of SOX's effects on funding and incentives (Chhaochharia and Grinstein, 2007; Engel *et al.*, 2007; Jain *et al.*, 2008; Kamar *et al.*, 2007; Kang *et al.*, 2010; Li *et al.*, 2008; Litvak, 2007; Wintoki, 2007). Thus, while the univariate times series analysis here differs from the panel data analyses common elsewhere in the literature, the literature itself suggests that stem cell technology innovation should demonstrate a clearer SOX related response than general innovation. Time series analyses allow ready graphical representation of the empirical methods here, and are a bridge for their later entry into panel data studies.

SOX's effect can be identified by comparing quantities of interest in base periods assumed to have been influenced by SOX with their value in control periods assumed to be free of influence. Existing literature differs in the length and timing of the base and control periods. Event studies such as Li *et al.* (2008) and Zhang

(2007) take short base periods associated with plausibly significant SOX-related occurrences and announcements, and usually extended control periods around the base periods. Doidge *et al.* (2009) use a long control and base period with a single cut-off point at the end of 2001 (as well as a more flexible sequence of annual cross sectional regressions). Engel *et al.* (2007) use both short and long base periods to classify times by SOX's impact. These periods are generally ultimately set according to the researchers' judgement.

It is not clear which dates to include in each period in view of SOX's decade long planning, passage, implementation, and delay (Gao *et al.*, 2009). The theoretical case for including, say, the date on which a senator issued a statement of regulatory intent, may be uncertain. Further, the effect may spill beyond the period hypothesised, or it may be delayed, or it may be a temporary reaction that is subsequently corrected. Alternative date classifications can lead to different conclusions. These classification problems are particularly severe for short periods. Whilst longer periods mitigate the difficulty, they are more likely to have influential non-SOX events within them, leading to problems in ascribing any changes to SOX.

Our approach to the classification problem is to use the data to estimate change dates in the number of US residents' patent applications over the period 2001 to 2009. Our first procedure estimates an autoregressive negative binomial count process in the presence of a structural change in trend and level where the change date varies across the whole period, leading to a series of change p-values. We examine the p-values to identify the absolute and relative importance of any break that occurred around the time of SOX. We use direct comparison of the p-values in the eighteen month period from July 2002 to December 2003 to identify the date at which a break was most likely. The coefficient estimates at that date are reported, as are Monte Carlo simulated p-values for the break coefficients. These values correct for the conditionality introduced in the raw p-values by the search procedure, and for the bias induced by small sample maximum likelihood estimation.

Our second procedure allows for multiple breaks and multiple patenting states. To identify them, we assume a constant probability of transition between Poisson states, with possibility of re-entry to previously exited states. The resulting hidden Markov model is estimated to give the most likely series of states over the whole period, and the coefficient estimates within each state. The estimation is performed for two and three distinct states.

The p-value testing finds that structural change occurred with higher probability around the time of SOX than elsewhere in the period. A trend change in patenting was most likely around July 2002, while a level shift was most likely around July 2003. In the two state hidden Markov model, a pre-SOX change is identified where patenting starts to increase from a very low level. The three state hidden Markov model identifies another change in July 2003, when the rate of patenting declines. Consistent with the earlier theoretical predictions following from the modelling assumptions, the rate corrects after two years to its previous process.

The timing of the patenting process break is consistent with other feasible non-SOX explanations. They include shocks to the patenting process that affect US and non-US patenters equally (unlike SOX), an exhaustion of the technological prospects of US patenters, a recent industry downturn that had driven many US innovators out of the market, and reduction in US government funding for stem cell research. We consider their plausibility and some empirical hypotheses that are closely related to them. Evidence is presented against them as exclusive explanations for the observed break.

Section 2 looks at the dynamic optimisation problem faced by innovators, section 3 performs the empirical analyses, and section 4 concludes.

2 Optimisations faced by innovators when SOX occurs

In this section, we present the optimisations faced by innovators before and after the passage of SOX. Innovation entails an irreversible investment, while SOX introduces uncertainty about costs that is resolved after a period of learning. We derive investment timings, and examine how much they are impacted by uncertainty, pace of learning, and discount rates.

2.1 Specification

Companies maximise expected profits through innovating and receiving income from the resulting intellectual property. Companies are indexed by i. They discount future income at a rate of d.

A company can choose to invest in a single innovation project at a cost that varies across companies. Company i has costs of C_i. Companies are aware of the project cost prior to investment. Investment is non-reversible and there are no resale opportunities at a value above the discounted stream of future income. Mathematically, the investment dummy $I_{i,t}$ for company i at time t is one or zero dependent on whether the company is invested or not, and satisfies $I_{i,1} = 0$ and $I_{i,t+1} \geq I_{i,t}$.

Innovation results in an expected constant stream of income of $R_{i,t}$ per period in perpetuity starting n_i periods after investment. $R_{i,t}$ is stochastic and drawn from distribution r_i after payment starts, being previously zero. $R_{i,t}$ is not known at the time of investment and is revealed only at the time payments start, when it becomes fixed in perpetuity. The distribution is known to the company at the time of investment. Thus, company i's investment return at time t is given by $R_{i,t} = R_{i,t-1} + (I_{i,t-n_i} - I_{i,t-n_i-1})r_i$ for $t > n_{i-1} + 1$, and $R_{i,t} = 0$ for $t \leq n_i + 1$.

On investment, companies protect their intellectual property by patenting. The number of patents following an investment is stochastic. The expected number is monotonically increasing in aggregate investment.

Companies enter the equity market and become subject to SOX provisions at the time they first receive profits and at all times subsequently. Such coincidence may occur if venture capitalists seek to realise their investments through the market when they start to produce revenue. In view of the importance of this exit route for early stage investors, we anticipate that many companies would use it. Our conclusions do not change if the timing is varied; what matters is that companies that have chosen to operate as innovators are affected by SOX's provisions. Indirect exposure through changes in the price of audit services, for example, leads to the same qualitative results. When companies are subject to SOX, their income per period is adjusted by an amount $S_{i,t}$. The sign and size of the effect is ambiguous, and certain company characteristics may be penalised under SOX while others may lead to financial benefit.

Companies are initially unsure about SOX's effect on income. They have assumptions about how they will update their prior distribution of the effect as information emerges over time, assuming that $S_{i,t}$ will have distribution function $F_{i,t}$ taking values in $s_{i,t}$. Companies anticipate that they will have sufficient information to form stable judgements of SOX's effect by time m and no later than the time of first payment n_i periods after investment, so that $S_{i,t+1} = S_{i,t}$ for all $t \geq \min(m, t_{inv} + n_i)$ where t_{inv} is the investment time.

A company that seeks to maximise expected future income has to choose if and when to innovate, using their subjective prior distribution for calculating expectations. They select the investment dummy $I_{i,t+1}$, $t = 2, 3, \ldots$ in the following Bellman equation:

$$
\begin{aligned}
V(I_{i,t}, & R_{i,t}, S_{i,t}) \\
&= \max_{I_{i,t+1}} (-(I_{i,t+1} - I_{i,t})C_i + I_{i,t-n}(R_{i,t} + S_{i,t}) \\
&\quad + \frac{1}{1+d} E(V(I_{i,t+1}, R_{i,t+1}, S_{i,t+1})),
\end{aligned}
$$

where V is the expected present value of the company's future income under the company's optimum investment plan.

2.2 Solution

For particular distributional assumptions and parameter values, this Bellman equation can be solved numerically. Without making such assumptions, we can deduce general behaviour algebraically.

In the absence of any SOX effect, $S_{i,t} = 0$. The problem faced by the company stays the same over time if no investment is made, so that investment either occurs in the first period or not at all. The condition for investment is that the expected net income from immediate investment exceeds the net income from non-investment.

When a SOX effect is first introduced, companies are uncertain about its magnitude and face a problem of choosing between immediate investment, delayed investment, and non-investment. Once all information is known about SOX's effect, the problem stabilises over time and so investment occurs at some stage during the learning process or not at all. Investment in period p_2 rather than in an earlier period p_1 is optimal if discounted expected net income given the state of knowledge in period p_2 is higher than expected net income given the state of knowledge in period p_1. If discounting is not large, post-SOX losses are considered possible, and learning occurs reasonably quickly, it will be advantageous to delay investment. For instance, suppose that p_2 represents the first time at which SOX's effects are known in full, when the company has determined the effect as a single unchanging point from the assumed distribution at time p_1. We define $v_{i,t}$ to be the stochastic discounted income when investment is made at time t. Then the optimisation criteria for delay from time p_1 to p_2 is that

$$E_{R,S}(v_{i,p_1}) < \left(\frac{1}{1+d}\right)^{p_2-p_1} E_{R,S}(v_{i,p_2}) \tag{1}$$

where the expectation is taken with respect to assumed future $R_{i,t}$ and $S_{i,t}$. Then the left hand side can be rewritten as

$$E_{R,S}(v_{i,p_1}) = \int_{s_+} E_R(v_{i,p_1})\, dF(S_{i,t}) + \int_{s_-} E_R(v_{i,p_1})\, dF(S_{i,t})$$

where s_+ is the subset of s_{i,p_1} defined by

$$s_+ = \{S_+ \in s_{i,p_1} : E_R(v_{i,p_1}|S_{i,p_1} = S_+) > 0\}$$

and s_- is the complement of s_+ in $s_{i,t}$,

$$s_- = s_{i,t} \setminus s_+.$$

The learning procedure anticipated between times p_1 and p_2 identifies a single point S_{i,p_2} in s_{i,p_1}, and investment will go ahead if and only if S_{i,p_2} lies in s_+, so

$$\int_{s_+} E_R(v_{i,p_1})\, dF(S_{i,t}) = E_{R,S}(v_{i,p_2}).$$

We rewrite equation (1) as

$$\begin{aligned}\int_{s_+} E_R(v_{i,p_1})\, dF(S_{i,t}) &+ \int_{s_-} E_R(v_{i,p_1})\, dF(S_{i,t}) \\ &< \left(\frac{1}{1+d}\right)^{p_2-p_1} \int_{s_+} E_R(v_{i,p_1})\, dF(S_{i,t})\end{aligned}$$

or

$$1 - \left(\frac{1}{1+d}\right)^{p_2 - p_1} < -\frac{\int_{s_-} E_R(v_{i,p_1})\, dF(S_{i,t})}{\int_{s_+} E_R(v_{i,p_1})\, dF(S_{i,t})}$$

Taking an example of parameter values of $p_2 = p_1 + 1$ and $d = 10\%$, the left hand side equals 0.09, so that a potential loss from ignorance that is quite small relative to the potential profit from early investment will lead to delay.

Hartman (2007) presents data from 2001 to 2006 on SOX related costs and companies' self-reported ability to predict them. The survey results show (pages 16-7) stabilisation of overall costs of operating as a public company after 2004, for companies with annual revenue over and under \$1 billion. The stabilisation is attributed to offsetting internal efficiencies, as actual external payments such as audit fees continue to increase (pages 2 and 19). They further show (page 14) a large increase between 2004 and 2006 in companies agreeing or strongly agreeing with the statement "...I am better able to predict costs associated with corporate governance reforms", from 38% to 65%. These results do not translate to an exact parameterisation for our model. However, they indicate narrowing distributions close to a point or slow moving deterministic process if the prediction process for future distributions has additional plausible assumptions, such as more weight being given to recent observations than older ones, importance being assigned to small changes in recent costs, and increased confidence in prediction resulting in diminishing importance of wide prior distributions.

Differences in costs, expected returns, prior and updated SOX distributions, and learning processes can generate differences in investment timing across companies in response to SOX. If these characteristics tend to be clustered within certain types of companies, then group behaviour can be observed in response to SOX. For example, risky companies may have a higher expectation of potential loss under SOX than less risky companies, and so a wait-and-see option may have a higher value to risky companies leading to relatively greater delays on investment.

After the end of the learning period, the investment problem stabilises for all companies, both those present when SOX was enacted and new entrants in subsequent periods. SOX's effect acts as a permanent adjustment to returns in the Bellman equation, with a positive adjustment lowering the required revenue to cross the investment threshold and negative adjustment raising it. Whether the threshold is crossed depends on company characteristics, and again group behaviour may be observed when characteristics are clustered. SOX's post-adjustment effect on investment may be positive or negative.

In summary, we expect the introduction to SOX to lead to an initial drop in aggregate investment due to delays in commitment to investment projects, followed by a spike as decisions are made. Delays in investment are easily triggered and may lead to a series of aggregate movements during the adjustment. Investment will then move to a rate higher or lower than prior to SOX's introduction depending on whether SOX increases or diminishes revenue. These long run effects are dependent on company characteristics and may act in different directions for different companies. The same shape of dynamic behaviour is anticipated in expected patents due to its monotonicity and shared sign with aggregate investment. The response in patents may be delayed by lags between investment and patenting. The patents literature has generally found a economically and statistically strong contemporaneous effect (Blazsek and Escribano, 2010; Gurmu and Perez-Sebastian, 2008; Hall *et al.*, 1986; Montalvo, 1997); an exception is Blundell *et al.* (2002) who find a slower effect under additional modelling assumptions.

3 Empirical analysis

Our empirical analysis examines the patenting rates for innovation in the area of stem cell technology. The stem cell technology industry is recently established, with only 22 issued patents referring to stem cells in their title by the end of 1995 (USPTO, 2010), shortly following the establishment of current industry leaders such as Geron, Osiris, and Viacord. The industry today remains relatively small, with Lysaght *et al.* (2008, Table 2) estimating 2007 commercial sales at $273 million, with average sales per operating company of $11 million. In the early 2000s, some of the industry's leading stocks exhibited considerable volatility (Salter, 2005). Investors at that time faced additional uncertainty relative to the situation today, in that the science was at a preliminary stage, product sales were negligible, and a number of the pioneering commercial enterprises in tissue engineering such as Organogenesis and Advanced Tissue

Sciences had filed for Chapter 11 bankruptcy. Investment, company numbers, and sales were all rapidly increasing and volatile (Salter, 2005, Table 3; Salter, 2005, Table 1; Lysaght *et al.*, 2008, Figure 1). These characteristics indicate that companies innovating in stem cell technologies would be among those the literature finds to be most susceptible to SOX's impact.

3.1 Data

Our data on patents is from the US Patent and Trademark Office online database at USPTO (2010). We use patent applications as our measure of patents rather than granted patents because there is a delay between application and issuance while the patent examiner assesses whether the application meets the criteria for granting a patent. The date of application thus better measures the time at which the decision to commercialise was made. The USPTO records both the date of application and the date at which the application information was published on their database which is later than the date of application. Thus, some recent patent applications are omitted from the database, with more recent times having a smaller proportion of their applications recorded. To avoid the risk of a fall in applications due to delayed coding interfering with our attempts to identify changes in applications due to other factors, we identify patent applications with the date at which their information was recorded on the database. This date is a noisy and lagged measure of the application date. Table 1 shows the summary statistics for the distribution of times between filing and publication for stem cell technology applications published in 2003. Half of all patent application filings are published within 39 weeks, and three quarters are published in just over a year. Some publications take place shortly after application, so that an event affecting the decision to apply for patents should be reflected in changes in applications at contemporaneous publication dates with a near complete effect over the following two years.

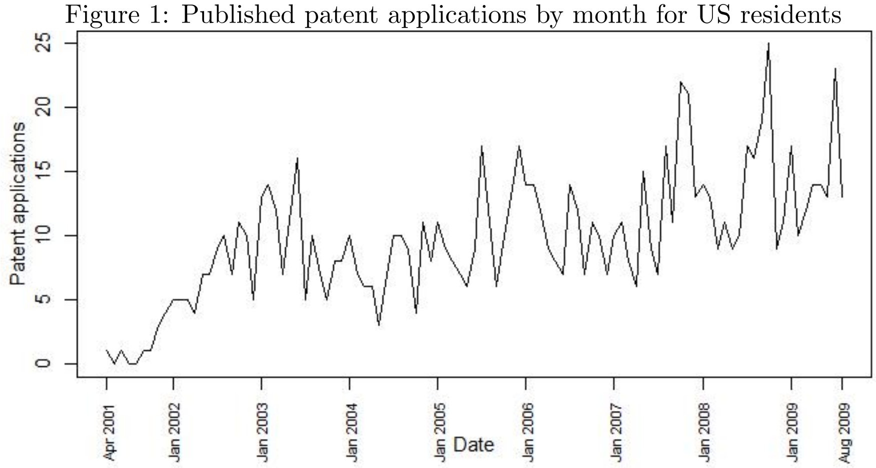
The USPTO database publishes applications only after March 1, 2001, with applicants after this date able to choose whether they wish to allow publication. Prior applications may not have been offered this choice, so would by default be deemed secret. Thus, most patent applications eligible for publication at much later dates would

Table 1: Summary statistics for the number of weeks between filing and publication of stem cell technology applications published in 2003

			Percentile			
Statistic	Mean	St.dev	50	75	90	95
Weeks	50	33	39	58	80	91

be made by applicants who could choose, whereas many patent applications eligible for publication at early dates may not have been published because the choice was not offered. This effect would be expected to lower the initial publication rate relative to later rates. Table 1 suggests that the effect will have substantially diminished by the middle of 2002 and all but vanished a year later. Its presence and timing complicates the interpretation of any change in the patent series as being due to SOX. We try to separate the two causes in section 3.4.1 by seeing whether the patenting of non-US applicants differed from that of US applicants, as both were subject to the USPTO regulations but generally only US applicants were subject to SOX.

Figure 1: Published patent applications by month for US residents



We used the USPTO online search facilities to identify patents with the exact phrase "stem cell" or "stem cells" in their title. The search was for published applications split by the month of publication for US resident applicants. Thus the code looked like

TTL/("stem cell" OR "stem cells") and PD/4/1/2001->4/31/2001 and ICN/("US").

The data covered the period from April 2001 to August 2009, and was accessed in September 2009. 982 patent applications by US residents were published in the period. Figure 1 shows publications of patent applications by US residents. The rate of publications increases rapidly until around the middle of 2003, then steadies until around 2005 when it steps up to a new plateau. The plateau lasts until around 2007 when a new period of accelerating publication begins, lasting until the middle of 2009.

An alternative to searching by individual patents is to look for patent classes mentioning stem cell technology within their patent schedule or definition, and then count the number of patents within them. There are six such classes, listed in table 2. The classes do not exactly coincide with all stem cell patents, so patents not relating to stem cells are included and some stem cell patents may lie outside the classes. The classes can be narrowed down to subclasses to mitigate the latter problem, but may worsen the former.

Table 2: US Patent and Trademark Office patent classes with "stem cell" or "stem cells" in the description or schedule

Patent class	Description
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
530	Chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products thereof
800	Multicellular living organisms and unmodified parts thereof and related processes
977	Nanotechnology

Generated by website searches on http://www.uspto.gov/web/patents/classification/ for "stem cell" and for "stem cells".

3.2 Estimation method

We present next the equations we will use in empirical estimation. They allow for the previous theoretical prediction of discontinuities in the patent process, through an autoregressive innovation metric combined with a current research input subject to breaks. We introduce two null hypotheses on the distribution of breaks in the patent process for testing an exceptional change around the time of SOX, and identify these changes with rolling p-value and hidden Markov chain estimations.

Our base specification has published patent applications P_t at time t following a random process with conditional expected value at any time dependent on a numerical measure of investment conditions I_t at time t, exogenous research R_t until time t, and the history $H_t = \{P_{t-1}, P_{t-2}, P_{t-3}, \dots\}$ of past patent rates until time t. Expected patents are a free combination of a proportion of patents in each previous period and exogenous research. The specific form of conditional expected patent numbers is multiplicative and exponential in lagged patents and exogenous research. The multiplicative metric for innovation has been analysed in Blundell *et al.* (1995). The exponents depend on innovation activity, which itself depends on investment conditions. Given investment conditions, the exponents are constant and the consequent growth in patents captures both market entry by potential innovators and their innovation activity. Exogenous research grows at an exponential rate. Thus we have

$$E(P_t|I_t, R_t, H_t) = A(I_t)(e^{gt})^{B(I_t)} \prod_{i=1}^{\infty} P_{t-i}^{c_i(I_t)}$$

where g is a constant, and A, B, and c_i are functions.

Some of new potentially patentable innovations will have been anticipated by previous patents, and others will have been subject to accelerated approval by the patent office. These two effects are captured by dividing the expected patent numbers by fractional powers of lagged patents. The form of the equation is therefore unchanged. The exponents may be negative as well as positive.

Changes in investment conditions are represented by changes in the equation's coefficients. Given the analysis in section 2, conditions are variable at the time of the introduction of legislation and during the period of investors' learning about its effects.

Our first empirical specification has a single shock occurring over the period. We assume that the exponents on the lagged patents are constant before and after the shock, while allowing the drift and level to change. The testable equation is

$$E(P_t|I_t, R_t, H_t) = \exp(a + bt + d_1 DS_{t>u} + d_2 DT_{t>u}) \prod_{i=1}^{\infty} P_{t-i}^{c_i}$$

where $DS_{t>u}$ is a unit shift equal to one for times $t > u$ and zero otherwise, and $DT_{t>u}$ is a trend change defined by $DT_{t>u} = t - u$ for times $t > u$ and zero otherwise. The stochastic distribution is taken to be negative binomial, and the estimation is by maximum likelihood. As logarithms are taken when calculating the negative binomial likelihoods under a multiplicative specification, we add one to all patent numbers before estimation.

The number of lags was determined by estimating the equation with up to twenty four lags. The Akaike Information Criteria and the coefficient significance of the highest lagged term were used to determine the optimal number of lags. The results are shown in the appendix. Four lags were taken as optimal.

If shocks to the patent process are persistent, the accumulating error may be collinear with a change in the time trend and estimator distributions may be different from their non-persistent versions (see Hamilton (1994, pages 497-501) for derivations with normally distributed errors). Persistent shocks may be misidentified as a break in the series. We tested for persistency in expected patent rates using a Zivot-Andrews test on the logarithmic series, which tests for unit roots when there may be a trend change or unit shift in the series. The statistic was -5.42, which is significant at five percent against a null hypothesis of a unit root.

We estimate the equation repeatedly with the value of u varying across the period under consideration. Estimations are not made for the first and last six months. Estimation is undertaken for the equation with a unit shift alone, a trend change alone, and both break types.

The procedure produces a series of p-values associated with an asymptotically valid normal test that the break variables are individually or dually equal to zero at each date. The p-values over the eighteen month period from July 2002 to December 2003 are directly compared to find the minimal one, and the parameter estimates at the corresponding break date calculated. The validity of the direct comparison relies on the assumption that our prior information is that a patenting incentive shock is equally likely to occur at any point in the period, implying a rising probability of incentive shock conditional on no shocks prior to the considered date.

The p-values may not accurately reflect the probability of a break in the generating process because of parameter biases in the finite sample maximum likelihood estimations. Moreover, as estimates of the probability that the patent process has a significant break during the eighteen month period, they do not allow for our search procedure. We want the probability of no break at the date conditional on that date having the greatest unconditional evidence of a break in the period, rather than the unconditional probability of no break at the date. To correct for MLE bias and allow for conditionality, we estimate the patent process without breaks and use the estimated parameters to generate a thousand Monte Carlo simulations of the process. For every simulation, we test for each type of break over the period and record the minimal p-values. The frequency of the simulated p-values lying below the actual data p-value is taken as an adjusted p-value for the break.

Our second empirical specification considers multiple shocks over the period, with possibly repeated entry, exit, and return to a fixed number of patenting incentive states. The incentive states have expected patent numbers with the autoregressive coefficients constrained to zero, that is,

$$E(P_t|I_t, R_t, H_t) = A_{j(t)}e^{b_{j(t)}t}$$

where $A_{j(t)}$ and $b_{j(t)}$ are the coefficients in state $j(t)$, the state prevailing at time t. The coefficients are specific to each state and do not have any relation to each other across states. The stochastic distribution of the patents is Poisson in each state. When in one state, the probabilities of moving to the same or another state in the following time period depend only on the current state, not the transition history or the date. These assumptions define a Poisson hidden Markov model (Zucchini and MacDonald, 2009).

We estimate the parameters in the second specification by maximum likelihood estimation. The most likely sequence of states is also estimated by maximum likelihood using the Viterbi algorithm. The algorithm calculates the most likely sequences of increasing lengths, given the estimation transition matrix and observed data, and ending in each possible state, using the Markov property to increment the length. For the sequences extending over the whole period, the maximum likelihood sequence is found by inspection of the likelihood of the sequences for each end state. Zucchini and MacDonald (2009) describe the mathematics of the algorithm and give a computer code implementation.

We estimate the model for two and three states. For a sequence of n periods, the number of state sequences is 2^{n} or 3^{n}. The most likely path differs little from many other paths, and its individual probability may be low. The estimates may be influenced by convergence thresholds even if they are small. There are plausibly multiple local maxima that may be identified by maximum likelihood. In order to ensure that the estimated sequence reflects a global maxima and its broad shape has a high concentration of probability among potential sequences, we repeat the estimation for multiple starting values for the Poisson rates in each state, selected either by visual inspection of plausible values or as starting, average, and end values of second or third quantiles of the data. The results we present are representative of the shape and timing of the shifts between states across most estimations.

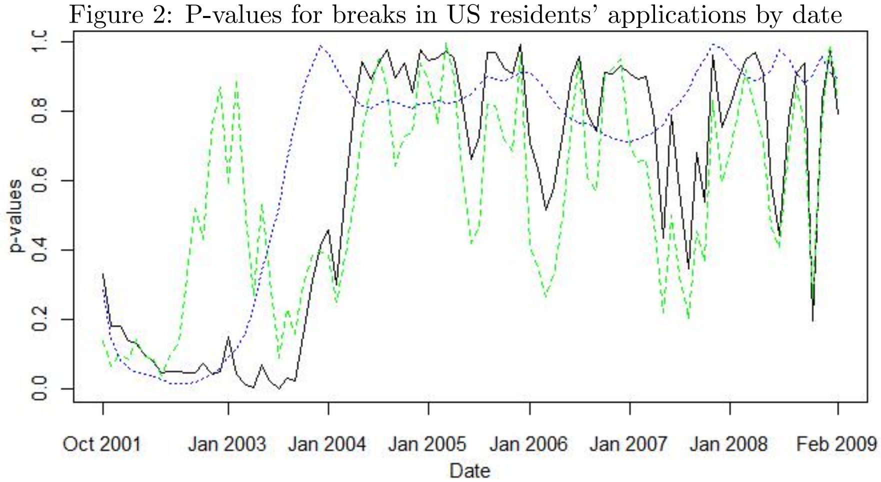
The estimation was performed in the R computer language (R Development Core Team, 2009) using the library packages Hmisc, urca, and MASS for the p-value estimation and testing, and the msm package for the HMM estimation. All R code for the modelling is available at the author's website[1], together with base data and simulated p-values.

3.3 Results

Figure 2 shows the p-values for unit, trend, and dual breaks (that is, breaks in either the unit or trend component) at dates throughout the period 2001 to 2009 for published patent applications by US residents. The solid line indicates values for dual breaks, the dashed line for unit shifts, and the dotted line for trend changes. The unit shifts are most likely to have occurred around the start of 2002, followed by the middle of 2003. The trend changes are most likely to have occurred in the middle of 2002. Changes elsewhere are unlikely. After allowing for correlations between the breaks, the dual break curve finds strongest evidence for a break occurring at dates from around the middle of 2002 to the last half of 2003. The strongest

[1] http://ebasic.easily.co.uk/02E044/05304E/sox_effect_on_innovation.html

Figure 2: P-values for breaks in US residents' applications by date



The solid line shows values for dual breaks, the dashed line for unit shifts, and the dotted line for trend changes.

evidence occurs around the second quarter of 2003.

Table 3 shows the coefficient estimates for each break date. The coefficients are evaluated at the minimal p-value from July 2002 to December 2003. The unit shift is most significant at July 2003, where it has a negative coefficient. It is significant at ten percent, but the adjusted p-value shows the coefficient has no significance. The minimal trend p-value is at July 2002, where the change is negative. The change is equivalent to an eleven percent reduction in expected patents compounded over time. It has an adjusted significance of eight percent. With both breaks included, the minimal p-value occurs in July 2003. The unit shift coefficient has a negative sign, marking a one-off reduction of 47 percent in the expected rate of patenting, while the trend change is also negative, equivalent to a six percent compounded reduction in the patenting rate. The adjusted probability that the coefficients are simultaneously zero is two percent.

The top panel of figure 3 shows the decoded states of a two state hidden Markov model applied to the patent data. There are two temporally connected states identified. The first runs for seven months from April to October 2001 and has low and roughly constant patenting rates. The second runs unbroken from November 2001 onwards and has an apparently increasing patent rate. The

Table 3: Coefficient estimates for breaks at the time of the minimum p-value in July 2002 to December 2003 inclusive

	1	2	3
Unit shift	-0.198 *		-0.643 ***
	0.116		0.176
Trend change		-0.115 **	-0.059 ***
		0.047	0.018
Time	0.006 ***	0.12 **	0.068 ***
	0.002	0.048	0.019
Constant	1.125 ***	0.038	0.74 ***
	0.205	0.497	0.245
Dependent(t-1)	0.285 ***	0.238 **	0.208 **
	0.099	0.101	0.101
Dependent(t-2)	0.008	-0.067	-0.069
	0.1	0.104	0.102
Dependent(t-3)	0.269 ***	0.186 *	0.156
	0.099	0.104	0.104
Dependent(t-4)	-0.095	-0.209 **	-0.218 **
	0.092	0.099	0.099
Break significance	0.087	0.015	0.001
Adjusted significance	0.522	0.084	0.017
Pseudo R^2	0.52	0.54	0.58
Box-Ljung p-value	0.98	0.9	0.89
Break date	Jul-03	Jul-02	Jul-03

Standard deviations are shown below the coefficients. *** denotes an unconditional p-value of less than 0.01, ** of less than 0.05, * of less than 0.1. Time is measured in number of months elapsed since March 2001.

bottom panel of figure 3 shows the decoded states for a three state HMM process. The early connected state to October 2001 is unchanged. A second state from November 2001 persists until April 2002, and then returns for a connected two year period from July 2003 to June 2005. The second state's sequence is interrupted by a third state which lasts unbroken until the second state is restored in July 2003. After exit from the second state in June 2005, the third state returns and persists until the end of the period. The third state has a higher apparent patenting rate than the second state after transition. It is not clear whether the time trend is higher or lower.

Figure 3: Decoded states for a two state hidden Markov model (top) and three state HMM (bottom) for US residents' published patent applications; states are connected by coloured lines

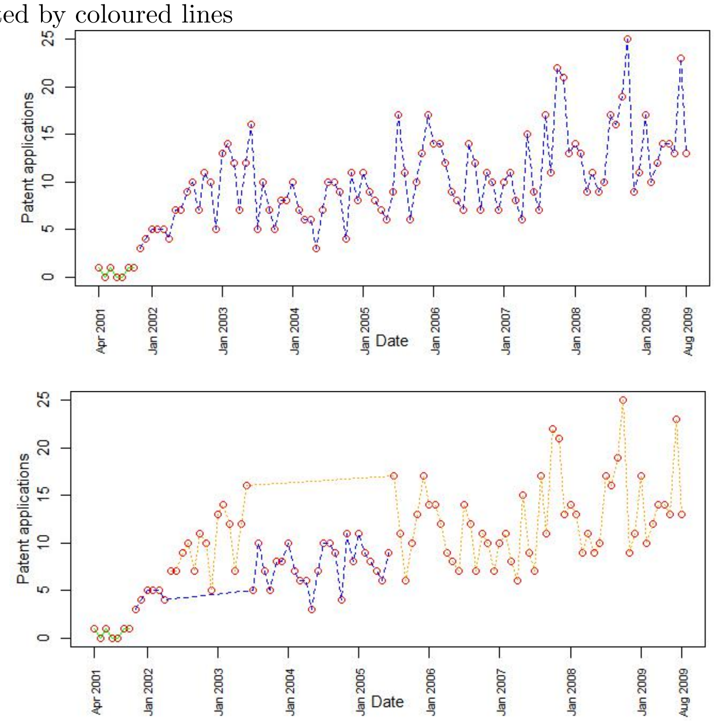


Table 4 contains the maximum likelihood estimates of the coefficients in each Poisson patenting state, showing the constant and time trend components of the expectation. The short-lived first state has a low rate throughout its duration under both the two state and three state specifications. The second state has a far higher constant component to the state expectation. For the three state estimation, the last state has a higher constant component but lower trend than the second state.

The observations indicate a large upwards shift in the patenting rate and trend in November 2001 away from the negligible patenting activity that existed until then. A further upwards shift in level, if not in trend, occurred in May 2002. The patenting state that emerged was interrupted temporarily from July 2003 to June 2005 by the restoration of the previous state. The timing of the July 2003 break is consistent with an adverse effect due to SOX.

Table 4: Coefficient estimates for the states in the two and three state HMMs on US residents' applications

	1	2
State 1		
Constant	0.209	1.004
Trend	-0.234	0.141
State 2		
Constant	9.819 ***	8.616 ***
Trend	0.088 ***	0.135 *
State 3		
Constant		11.194 ***
Trend		0.062
Date of first entry into state 1	Apr-01	Apr-01
Date of first entry into state 2	Nov-01	Nov-01
Date of first entry into state 3		May-02

*** denotes an unconditional p-value of less than 0.01, ** of less than 0.05, * of less than 0.1. The p-values are for an asymptotically valid chi-squared test using parametrically bootstrapped standard deviations with 100 bootstraps. Time is measured in number of months elapsed since March 2001 multiplied by 0.1.

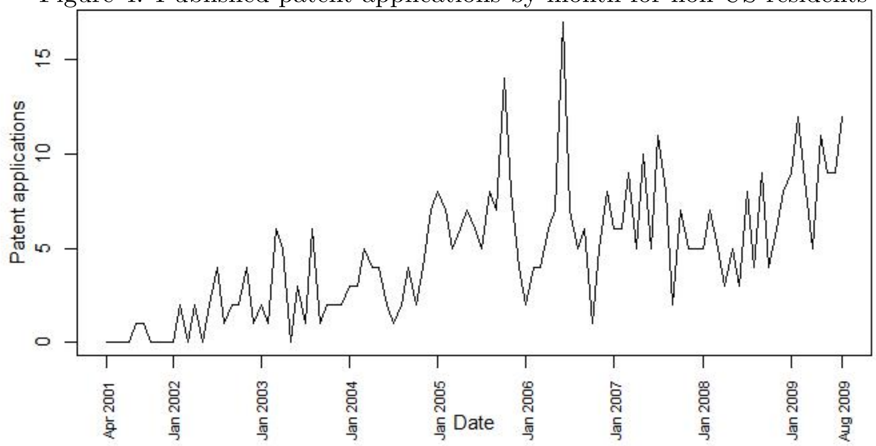
3.4 Non-SOX explanations for the patenting shifts

The previous section has found evidence of a break in the patenting rates of US residents in stem cell technology. The timing is consistent with an effect due to SOX. We also have a plausible theoretical explanation for an effect. We can strengthen the support for a link by showing the likelihood of alternative explanations is low.

3.4.1 Alternative explanation one: the change was due to factors affecting both US and non-US resident patenters

A number of explanations arise from factors affecting the patenting of both US and non-US residents. Among them are an exhaustion of commercialisable ideas in stem cell technologies, a shift of global investor preferences against funding its innovation, a shift against speculative investment generally, a reduction in US demand for stem cell technologies, processing delays at the US patent office, or an increasing proportion of applicants choosing to publish their applications over time.

Figure 4: Published patent applications by month for non-US residents

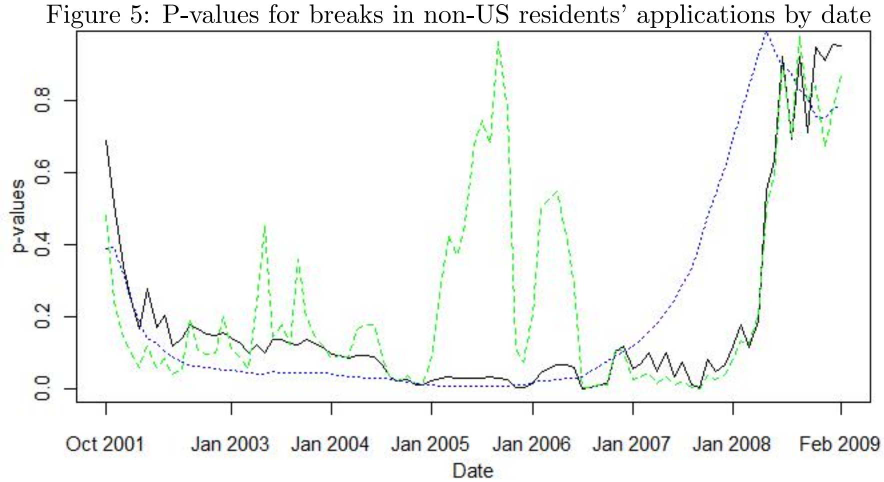


Under this class of explanations, the incentives or ability of non-US residents to patent in stem cell technologies is reduced at the same time as those of US residents. A break in non-US residents' published patent applications is likely to occur and approximately coincide with the previously observed breaks. The earlier empirical equations form the basis for testable hypotheses on a break in their published patent applications.

The data for non-US residents is also from the US Patent and Trademark Office. It is shown in figure 4. The publication rate rises until around the start of 2003, then stabilises until the end of 2004 when it begins to increase rapidly, lasting until the middle of 2006. It undergoes a possible downwards shift in the level of the series. It then rises, falls, and then rises again until the middle of 2009. The observed pattern is not clear; it could alternatively be explained as a roughly constant growth rate with a period of greater volatility around the end of 2005 and start of 2006.

Figure 5 shows the p-values for unit shifts (dashed line), trend changes (dotted line), and dual breaks (solid line), estimated with an autoregressive lag of two. Unit shifts are most likely at the end of 2004, and in the second halves of 2006 and 2007. The period from the middle of 2002 to the end of 2003 has relatively less evidence of a break. Trend changes are most likely to have occurred in 2005. The most probable times for a break in at least one of the series are

Figure 5: P-values for breaks in non-US residents' applications by date



The solid line shows values for dual breaks, the dashed line for unit shifts, and the dotted line for trend changes.

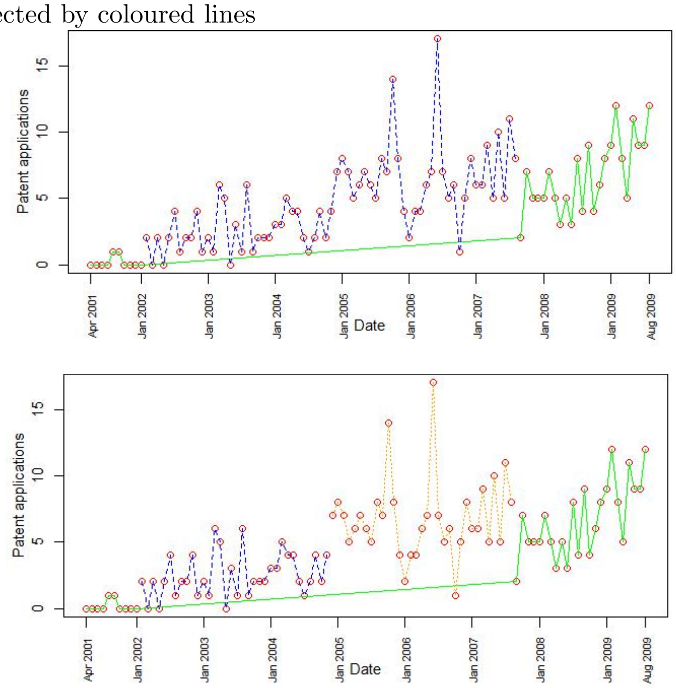
at the ends of 2004 and 2005, and the middle of 2006. The SOX period is relatively less likely to have experienced a break.

The results contrast with the observed decline in the US residents' patent rate at the time of SOX. The two results are consistent with the decline's cause acting only on US residents. They provide evidence against the class of alternative explanations to SOX that explain the decline in terms of globally effective factors.

The decoded states for a two state hidden Markov model of the non-US patent data are in the top panel of figure 6. The initial state lasts from April 2001 to January 2002. From February 2002 it undergoes an extended break and is restored only in September 2007. It then endures to the end of the period. The intervening second state lasts unbroken for over five and a half years. It has an apparently higher level than the first state. They both have an upward trend. In the three state model shown in the bottom panel, the first state is unchanged from the two state model. The second state only occurs for the period from February 2002 to November 2004. It has a higher apparent rate than the first state. After its end until the restoration of the first state, a third state occurs with apparently even higher rate and uncertain trend.

We do not see any evidence of a downward break in the period around SOX, or any break at all. The analysis produces a similar

Figure 6: Decoded states for a two state hidden Markov model (top) and three state HMM (bottom) for non-US residents' published patent applications; states are connected by coloured lines



conclusion to the p-values break results. It is less likely that globally applicable factors were the main cause for the reduction in US residents' patent rates, and more likely that SOX was.

3.4.2 Alternative explanation two: there was a natural patenting downturn due to exhaustion of ideas, but only in the US

A further explanation for the observed break is based on the pattern of emergence and exhaustion of patentable ideas. Ideas are posited to lead to patents. Ideas start slowly at first as a technological idea is first investigated, then as the most promising prospects are discovered the generation of patentable ideas accelerates, and finally the prospects begin to be exhausted and the rate flattens. The observed break corresponds to the beginning of the gradual exhaustion and deceleration.

In order to distinguish this explanation from the general global explanations just discussed, we have to posit that the decline is in the US alone. The situation might arise if US innovators are innovating in a different type of patents than foreign innovators, for example if they are far more technologically advanced. The condition requires that technological innovation does not rapidly spill across borders, which is open to theoretical and empirical question.

The explanation suggests a trend change in the patenting rate without a level shift in it. The rolling p-value analysis earlier found evidence for a trend change but no significant evidence of a unit shift. The hidden Markov model estimation by comparison found that there was a temporary downwards level shift in the aftermath of SOX. Thus, the evidence available so far provides mixed evidence against the exhaustion hypothesis.

We investigate further by examining behaviour after the downturn. Under the exhaustion hypothesis, the rate of innovation will decline further after the initial transition. We test empirically for the presence of further downturn by modifying the form of expected patents to

$$E(P_t|I_t, R_t, H_t) = \exp(a + bt + et^2 + d_2 DT_{t>u}) \prod_{i=1}^{\infty} P_{t-i}^{c_i}$$

where the period assessed is from August 2003 to August 2009. Our first specification has the restriction $e = 0$ with u set at the mid point between the break date and the end of the period, ie August 2006 (so allowing for a late break). Our second specification has $d_2 = 0$ (allowing for a quadratic downturn in time with linear time as a covariate), and our third has $b = 0$ and $d_2 = 0$ (allowing for a quadratic downturn in time without a linear covariate).

Table 5 shows the sign and significance of the late trend change and quadratic terms in the maximum likelihood estimations. The sign on the late trend change is negative, but the coefficient has low statistical significance. The same is true for the quadratic time term in the presence of a linear time trend. If quadratic time is present without a linear time trend, it has a positive coefficient and is highly significant, probably capturing some of the linear trend effect. In summary, we again find limited evidence for the exhaustion hypothesis as it is presented here.

Table 5: Coefficient estimates for the states in the two and three state HMMs on US residents' applications

Variation from a linear process	Sign, p-value of the non-linear term
Late trend change	-, 0.63
Month^2 (with covariate month)	-, 0.55
Month^2 only	+, 0.00

3.4.3 Alternative explanation three: the earlier market downturn reduced perceived incentives for patenting

The observed change in the patenting process may alternatively be attributed to a downturn in market prospects. Under this hypothesis, there was a loss of confidence or funding in the market, and many innovators exited the market. There is data presented in Lysaght *et al.* (2008) showing a decline in the financial performance and size of the tissue engineering market prior to SOX, although the stem cell sub-sector experienced employment growth and was financially sheltered by its pre-commercial status.

After a market decline and financial rationing, if remaining financiers are reasonably accurate at assessing financial prospects of innovations the residual funding should be allocated to innovations offering better financial prospects than innovations funded prior to the rationing. By contrast, SOX has been associated with reduction in corporate funding for new, small, and high growth companies, who may be expected to produce innovations with better than average, if risky, prospects. Thus, the SOX and market downturn explanations for patent number changes have different implications for the prospects of the remaining innovations relative to innovations prior to the downturn.

We may noisily measure the financial prospects of patents by the number of patents citing them. The propositions and measure allow us to form a testable hypothesis associated with the downturn conjecture, that the rate of citing of new patents was higher after the process change than before it. The alternative hypothesis associated with a SOX effect is that the rate of citing was the same or lower after the process change.

Table 6 shows the citation rates for stem cell technology patents whose applications were filed from April 2001 to March 2002 inclusive, compared with those filed between April 2003 and March

Table 6: Rate of citing of patents whose applications were filed April 2001 to March 2002 or April 2003 to March 2004 inclusive, split by issue year

	Applications filed in 2001/2		Applications filed in 2003/4	
Issue year	Counts	Average citations	Counts	Average citations
2002	1	1		
2003	5	4.8		
2004	15	5.3		
2005	15	2.5	1	0
2006	17	1.3	5	0.6
2007	6	2.2	5	1.2
2008	3	1	12	0.2
2009	5	0	9	0.1
2010	1	0	8	0
Total	68	2.6	40	0.3

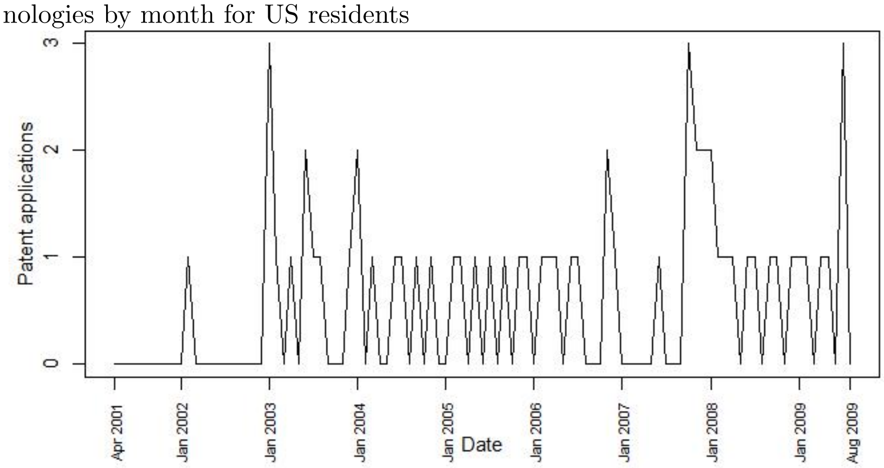
Data is from the US Patent and Trademark Office. The website search term was, for example, TTL/("stem cell" OR "stem cells") and APD/4/1/2001->3/31/2002 and ISD/4/1/2006->3/31/2007.

2004. Data is from USPTO (2010). The rates are given for all citing patents up to July 2010, and are split by the year of patent issue and for all issue years combined. The combined citation rate is far higher for the earlier period of filing. The higher combined rate may be possibly attributable to a longer post-issue period for earlier filed patents and hence more exposure and opportunities for citation. The length of the period since issue is controlled by the comparison of patents issued in the same year. These rates are consistently higher for the patents filed in 2001 to 2002. We find no evidence of an increase in the citation rate for patents filed after the observed break, or that financial prospects as proxied by citation rates picked up after it. The result weakens support for the hypothesis that a financial downturn was the main driver of the observed changes in the patent process.

3.4.4 Alternative explanation four: the change can be attributed to US Government funding cuts for human embryonic stem cell research

A further candidate explanation for the observed change in the patenting process is that legislative or federal funding activity relating to human embryonic stem cell technologies in the United States affected the rate of patent applications. In 2001, the US administration restricted federal funding for research in human embryonic stem cells (United States White House, 2001). The decision may have driven down innovation in human embryonic stem cell technologies directly, and indirectly affected companies producing other stem cell technologies (see Salter (2005, page 8) for a description of a contamination effect between the two forms of technology).

Figure 7: Published patent applications in human embryonic stem cells technologies by month for US residents



The mechanism is feasible, but it seems implausible that it would have a sufficiently large effect to be the only cause of the observed process change. Firstly, federal research funding was restricted on stem cell lines from embryos destroyed after the date of the restriction, but not prior to the date. Thus, the restriction was partial. Secondly, it did not affect privately funded research. Thirdly, the number of human embryonic stem cell patents was very small compared with the number of general stem cell patents. From a search on the US Patent and Trademark Office database, the cumulative number of US residents' patent applications between April 2001 and August 2003 with "human embryonic stem cell" or "human embryonic stem cells" in the title was just ten compared with 185 general stem cell technology patents. Even if the federal funding restriction stopped most innovation in human embryonic stem cell technology, the direct effect on the broader innovation group would be very limited. Fourthly, if there is a contamination effect on non-embryonic innovation from the restriction, it would have to be very large and persistent to account for the observed process change. There seems little prior reason to believe in such an effect. Fifthly and finally, insofar as it is possible to determine a process shift from the low numbers of human embryonic patents in figure 7, it does not seem to be any greater than that affecting the general stem cell patent series.

4 Conclusion

We have presented and partially solved a optimisation faced by innovators in the presence of a SOX caused change to investment incentives. Postponement of investment due to temporary uncertainty means double breaks of a decline and correction are more likely than single breaks in the time series of innovation investment. The long term effect is ambiguous. Empirically, we found using a p-value time series and a hidden Markov model that the observed data showed behaviour consistent with these theoretical results, with the latter method finding a reversion to the pre-SOX process after two years. We considered several feasible non-SOX explanations for the break and found available evidence suggested they were unlikely to explain the change on their own.

The optimisation assumes that investors are risk neutral. The assumption may be replaced with constant risk aversion to reinforce the initial post-SOX dip in investment in the presence of learning. The dynamic delay effect would not lead to any investment decline under correctly anticipated constant risk, whereas constant risk aversion would result in a decline, potentially allowing for assessment of these two effects' relative importance in future work.

Investor-manager identity is assumed in the optimisation, so that managerial perception of increased personal costs of risky activities after SOX or uncertainty about them are combined with investor assessment of income changes and corresponding uncertainty. The manager and investor optimisations may be separated giving rise to a two step decision process. The approach may bring out agency tensions, enrich the dynamics, and present new testable implications.

Various small departures from the empirical model's assumptions were tested during this paper's preparation, being rejected as imperfect models of count data although they may be more valid for other data sets. We tested additive instead of multiplicative patent forms and used random walk processes for patent emergence with sandwich and GARCH errors. The conclusions were not altered.

Most analyses of SOX's effects are based on panel data rather than a single time series. We may extend the approach here to patent panel data, using multivariate count data and HMM models which are established in the literature. The dummies that are used in the SOX literature based on differences-in-differences may not enter these count data models in additive form making their removal more complex, if possible at all. Thus, relative to the existing literature it may be more difficult to isolate SOX breaks and separate SOX effects from other effects, and the graphs presented here may not readily translate into a panel data analysis for visual examination. Preliminary data investigations indicate that non-stem cell technology patent series also exhibit breaks around the time of SOX.

Future work could examine SOX-related causes for the observed break in more detail. The reduction in available funds for patenting is one candidate. There are other possible links such as companies avoiding patenting in order to avoid value creation and so remain below the threshold for accelerated SOX filing (see Gao *et al.*, 2009). Larger theoretical models and multivariate empirical models may expose the links.

Appendix: Autoregressive diagnostics

Table A1: AIC and highest lag p-values by AR order for negative binomial models of patent applications

	US applicants		Non-US applicants	
Lag	AIC	Lag p-value	AIC	Lag p-value
1	424.6	0.09	375.1	0.05
2	426.6	0.9	374.4	0.1
3	427.5	0.31	376.2	0.61
4	426.7	0.08	378.1	0.83
5	428.6	0.77	379.9	0.67
6	430.3	0.62	381.9	0.98
7	432.1	0.66	382.6	0.24
8	432.6	0.21	382.2	0.13
9	434.3	0.63	383.6	0.44
10	436.3	0.95	384.5	0.28
11	437.4	0.33	386.4	0.73
12	438.9	0.49	387	0.24
13	436.6	0.04	388.3	0.42
14	434.5	0.05	390.3	0.93
15	435.8	0.38	384	0
16	434.5	0.07	386	0.96
17	436.5	0.94	386.5	0.23
18	434.7	0.05	386.8	0.19
19	435.7	0.32	388.5	0.62
20	437.4	0.58	389.2	0.25
21	438.5	0.34	391.1	0.76
22	437.9	0.1	393.1	0.93
23	438	0.17	394.8	0.57
24	433.3	0.13	390.8	0.17

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