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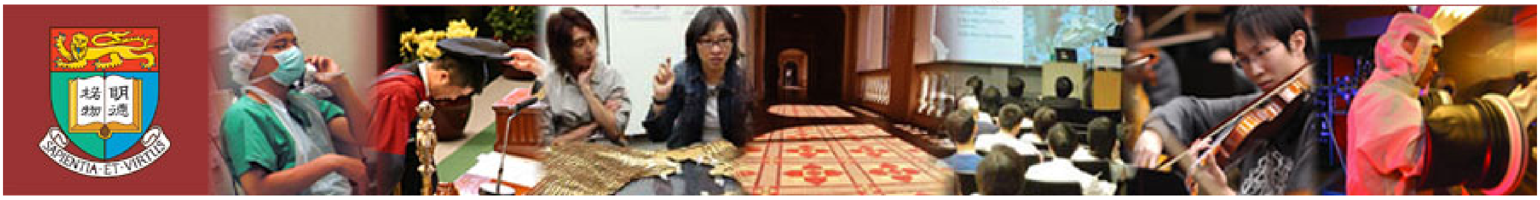

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Technological Innovations and Aggregate Risk Premiums†

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Technological Innovations and Aggregate Risk Premiums

Abstract

In this paper, I propose that technological innovations increase expected stock returns and premiums at the aggregate level. I use aggregate patent data and research and development (R&D) data to measure technological innovations in the U.S., and find that patent shocks and R&D shocks have positive and distinct predictive power for U.S. market returns and premiums. Similar patterns are also found in international data including other G7 countries, China, and India. These findings are consistent with previous empirical studies based on firm-level data, and call for further theoretical explanations.

JEL classification: E44; G12; O30

Keywords: Return predictability; Patents; Research and development; Technology shocks; Technological innovations

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1 Introduction

This paper examines the effect of aggregate technological innovations on expected market returns and premiums. In the finance literature, most attempts to explain the time series of market returns are based on macroeconomic and financial variables.[1] Since technological innovations are the main driving force for economic growth and fluctuations, they may provide valuable information about the dynamics of aggregate wealth from a distinct perspective.[2] The empirical analysis suggests that, indeed, technological innovations are able to predict market returns and premiums in recent decades.

I propose that technological innovations drive up expected market returns and premiums for several reasons: First, technological innovations raise the expected productivity and profitability of the representative firm. Second, technological innovations improve overall efficiency and reduce investment costs. Lastly, technological innovations work as options with returns more volatile than physical investments. Since the representative firm's expected stock returns equal expected investment returns,[3] they rise with more technological innovations. All these arguments imply a positive relation between technological innovations and expected market returns as well as premiums.

The hypothesis is empirically testable using patent data and research and development (R&D)

[1] An incomplete list includes the lagged returns (Fama and French, 1988a), the dividend-price ratio (Shiller, 1984; Campbell and Shiller, 1988; Fama and French, 1988b), the term spread and default premium (Fama and French, 1989), the relative bill rate (Campbell, 1990, 1991), the book-to-market ratio (Kothari and Shanken, 1997), the dividend-earnings ratio (Lamont, 1998), the aggregate consumption to wealth ratio (Lettau and Ludvigson, 2001), the share prices to GDP ratio (Rangvid, 2006), and the labor income to consumption ratio (Santos and Veronesi, 2006).

[2] Since Solow (1957), the economics literature has long recognized technology development as an important component of economic dynamics. Technological progress comes from endogenous efforts (e.g., R&D expenses that generate inventions) and exogenous incidents (e.g., new discoveries due to accidents), and both types of advances are found to explain economic growth and fluctuations (e.g., Romer, 1986, 1990; Greenwood, Hercowitz, and Krusell, 1997, 2000). Moreover, Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2001) argue that the information-technology (IT) revolution caused global stock markets to drop in the 1970s and then rebound in the 1980s. Pástor and Veronesi (2008) propose that the adoption of uncertain technological revolutions drives stock price bubbles.

[3] The equivalence between investment returns and stock returns has been proved in Cochrane (1991) and Restoy and Rockinger (1994). Lately, Liu, Whited, and Zhang (2008) and Chen and Zhang (2009) show that such a relation provides a good description of the cross-section of expected stock returns.

data as proxies of technological innovations.[4] I note that patent data are more informative than R&D data in many aspects, but have rarely been considered in the finance literature.[5] First, patents are realized innovations ready to be utilized for business interests. Second, the territorial principle in patent laws makes patent data a more precise proxy of a nation's technological progress. Third, patents are the intangible assets most actively traded in intellectual property markets (Lev, 2001). As a matter of fact, the first exchange traded fund (ETF) based on patents, the Claymore/Ocean Tomo Patent ETF, was just launched on December 15, 2006.

I use total patents and accumulated industry R&D expenses in the U.S. to measure aggregate technology level, and use their growth rates to measure technological growth. Then, I detrend these two growth rates to estimate patent shocks and R&D shocks, as two proxies of technological innovations. Predictive regressions indicate that both patent shocks and R&D shocks have significant predictive power for the real and excess returns on the Standard and Poor's 500 (S&P500) index and the Center for Research in Security Prices (CRSP) value-weighted index, in both short and long horizons. The slope coefficients for lagged patent shocks and R&D shocks are positive with economic and statistic significance, and the associated *t*-statistics are not affected by the existence of other predictors. The adjusted R-squares of one-quarter ahead predictive regressions are well above five percent. These empirical findings survive several robustness checks, and suggest that technological innovations are able to explain a specific, substantial part of expected market returns and premiums. Moreover, consistent with my earlier argument, patent shocks are found to outperform R&D shocks in predictive ability.

I then extend the empirical analysis to available international data. Using China's patent data, I find that China's patent shocks significantly predict the real and excess returns on China's stock index. On the other hand, I examine the effect of R&D shocks on stock returns in Canada, France,

[4] Griliches (1984, 1988) and many other studies find that these two data sets are able to explain economic growth. Moreover, there exist other technology statistics including the number of scientific journal articles (Price, 1963), the number of scientists and engineers (Gort, 1969), and the number of books published (Alexopoulos, 2006).

[5] Pakes (1985), Rossi (2005), Seru (2007), and Acharya and Subramanian (2007) are the only four to my knowledge, and the latter three focus on corporate finance issues.

Germany, India, Italy, Japan, and U.K. ("G6 plus India," henceforth). I find that country-specific R&D shocks are positively correlated with future market returns and premiums in all countries except France. The results from pooled regressions indicate that country-specific R&D shocks significantly predict market returns and premiums in G6 plus India. All these findings support the technology-driven predictability from an international perspective.

Note that technological innovations used in this study differ from the Solow (1957) residual in many aspects: First, the Solow residual contains all unexplained disturbances, and some of them (e.g., wars, oil crises, fiscal shocks, and natural disasters) are conceivably irrelevant to technological progress.[6] Second, the Solow residual includes both temporary and permanent shocks, while technological innovations mainly have permanent effects on the real economy. Third, the literature suggests a negative effect of the Solow residual on future market returns,[7] while technological innovations are found to positively correlate with future market returns in this study.

This study adds to the literature from three perspectives. First, previous studies focus on the relation between technological innovations and stock returns at the firm level (e.g., Pakes, 1985; Austin, 1993; Lev and Sougiannis, 1996; Deng, Lev, and Narin, 1999; Chan, Lakonishok, and Sougiannis, 2001), while I document the time series predictability of stock returns at the aggregate level. Second, I propose to use total patents and R&D expenses to measure aggregate technological innovations, which appear to be very effective predictors for market returns and premiums. Finally, I provide international evidence for the technology-driven predictability, and show that the positive connection between technological development and financial markets extends beyond the U.S. data.

The rest of this paper is organized as follows. I first detail how I construct two proxies

[6] While Solow names all of the unexplained part of total production as "technical change," Denison (1967) points out the necessity of distinguishing technology shocks from non-technology shocks. Basu and Fernald (2002) also argue that productivity shocks and technology shocks are distinct concepts.

[7] For example, Balvers, Cosimano, and McDonald (1990) show that current output level correlates negatively with future market returns in a general equilibrium model. Kothari, Lewellen, and Warner (2006) find a negative relation between aggregate earnings surprises and subsequent market returns.

for technological innovations—patent shocks and R&D shocks—in Section 2. Then, I employ predictive regressions to empirically test if these two shocks explain future market returns and premiums in Section 3. I implement the same analysis for international data in Section 4. Section 5 summarizes my findings and connects them to related models in the existing literature.

2 Aggregate technological innovations

2.1 Aggregate patents and R&D expenses

Total patent numbers and accumulated aggregate R&D expenses are used as two proxies for the aggregate technology level as they are well-defined and specific to sciences and technologies. As do previous studies considering macroeconomic factors, I use quarterly patents and R&D expenses in empirical analysis. This choice of data frequency not only accommodates the lead time between technological inventions and productivity changes, but also delivers a bigger sample.[8]

For patent data, I compute each quarter's "patent flow" as the number of all types of patents filed in each quarter (successful patent applications), which are available since 1976Q1, from the U.S. Patent Full-Text and Image Database (PatFT) of the U.S. Patent and Trademark Office (USPTO). Following the literature (e.g., Pakes and Griliches, 1984; Pakes, 1985; Shea, 1998; Hall, Jaffe, and Trajtenberg, 2001), I use the application dates of patents as effective dates, and count the number of patents filed in each quarter as the technology progress in that period. I recognize Abel's (1984) comment that using application dates for effective timing is a strong assumption. Nevertheless, as argued in many aforementioned papers, new technologies should start to affect real production once they appear. For example, consumers often find new products labeled "patent pending," as the intellectual properties of inventors are protected since the filing dates.

In collected patent flows, I find four inappropriate outliers (1982Q2-Q3 and 1995Q1-Q2) that appear to be unreasonable jumps, and substitute interpolated values for them. Also, since there

[8] Due to limited government statistics, most technology statistics are reported annually and can be traced back only to the 1950s and 1960s, delivering only about forty to fifty sample points.

exists an examination period (about two to three years on average) between the application date and issue date of each patent, I estimate patent numbers in the period 2005-2007 based on the application data available from the Published Applications Database of the USPTO. Such an estimation of recent patent numbers, however, does not affect my conclusion as almost identical results based on older samples have been reported in the earlier versions of this paper. Because patent data before 1976 are unavailable from USPTO databases, I refer to Hall, Jaffe, and Trajtenberg's (2001) data set for an estimate of 4,065,811 as the base number of total patents filed by the end of 1975. Finally, I add quarterly patent flows to this base number and obtain a time series of "patent stock" as a proxy for technology level in 1976Q1–2007Q4, which is illustrated in the upper panel of Fig. 1.

As for the R&D-based proxy, I compute quarterly "industry R&D flows" as quarterly industry R&D expenses by (1) summing up all firms' R&D expenses reported in the Compustat database in each quarter and (2) transforming each quarter's expenses into 1996 dollars. Quarterly R&D expenses in the Compustat database are available only since 1989Q1, so I resort to *National Patterns of Research and Development Resources: 2003* published by the National Science Foundation (2005) for an estimate of 2,799 billion 1996 dollars as a base for all industry R&D expenses prior to 1989. By adding quarterly industry R&D flows to this base, I obtain a time series of "industry R&D stock" for the period 1989Q1–2006Q4 as shown in the upper panel of Fig. 1.

Then, I compute logarithmic patent growth and R&D growth (i.e., the logarithmic growth rates of patent stock and industry R&D stock) as r^{pat} and r^{rd}, respectively.[9] In the lower panel of Fig. 1, I plot r^{pat} and r^{rd} and observe the following: First, similar to most macroeconomic variables, both time series are fairly persistent; second, they demonstrate significant co-movement prior to 1999. Declining R&D growth since 1999 could be attributed to the R&D out-sourcing wave since the 1990s and the dropping-off of internet companies after the burst of the internet

[9] In the calculation of patent growth and R&D growth, I adjust potential seasonality in patent numbers and R&D expenses using the one-sided moving average method, which is free from the forward-looking bias. The X-11 adjustment method is also considered and delivers similar results in unreported tables.

bubble.[10]

Some issues about using patent growth and R&D growth to measure aggregate technological growth are worth mentioning. First, I assume that the reported R&D expenses result from firm managers' rational decisions following Pakes (1985) and others. In other words, there is no irrational R&D bubble. Second, I recognize that not every dollar in R&D expenses leads to new inventions, and different patents have different impacts. Nevertheless, I refer to the "law of large numbers" argument proposed in Scherer (1965, 1984) and Griliches (1990, 2000), and treat all patent numbers or R&D dollars as random variables from one identical distribution. By summing up all patents and R&D expenses, I expect to average out idiosyncratic noises and obtain good measures of aggregate technological growth.

2.2 Patent shocks and R&D shocks

I propose the following two measures for technological innovations by detrending patent growth and R&D growth:

$$Tech_t^1 = ln(r_{t-1}^{pat}) - \frac{1}{4}\sum_{h=1}^{4} ln(r_{t-h-1}^{pat}) \tag{1}$$

$$Tech_t^2 = ln(r_{t-1}^{rd}) - \frac{1}{4}\sum_{h=1}^{4} ln(r_{t-h-1}^{rd}), \tag{2}$$

where $Tech^1$ denotes patent shocks and $Tech^2$ denotes R&D shocks. My approach is motivated by Griliches (1984) and Campbell (1990, 1991) and aims to stochastically detrend patent growth and R&D growth to capture the fluctuations in technological progress.[11] The length of the moving

[10] Brown, Fazzari, and Petersen (2008) report that the dramatic R&D boom in the 1990s is driven by young, hi-tech firms that can easily access external financing in those years.

[11] Griliches uses the annual data of 157 firms and constructs patent surprise and R&D surprise based on first-order difference. Campbell uses the moving average method to construct relative bill rate because the bill rate is a smooth time series with stochastic trends. The moving average method is simple and free from subjective model selection and forward-looking bias. Moreover, I adopt a univariate approach, as advocated by Chen, Roll, and Ross (1986), in constructing technology shocks because I do not find any economic variable forecasting patent growth and R&D growth. Nevertheless, I recognize the existence of more complicated measures of technology shocks proposed in the macroeconomics literature (e.g., Gali, 1999; Basu, Fernald, and Kimball, 2006), which heavily rely on model specifications and estimations.

window is set to be four due to quarterly frequency. Nevertheless, I also consider other detrending methods including eight-quarter moving averages and rolling AR(1) and obtain similar results as reported in Section 3.3. In addition, I impose one quarter lag in constructing the above shocks to accommodate the lead time between inventions and their impacts on real economy, if any. As shown in Fig. 2, $Tech^1$ and $Tech^2$ are autocorrelated as many economic shocks in the macroeconomics literature (e.g., King, Plosser, and Rebelo, 1988).[12] Moreover, the time series of patent shocks presents stationarity in mean without a significant trend, so it is free from the "patent application fad" suggested by Jaffe and Lerner (2004).

3 Empirical tests

3.1 Testing strategy

My testing strategy is to regress the real and excess returns of the market portfolio on lagged variables including patent shocks, R&D shocks, and other predictors. Since I employ unconditional regressions, the coefficients associated with lagged patent shocks and R&D shocks can be interpreted as the "average response" of market returns to technological innovations. If the proposed relation is true, these coefficients should be significantly positive.

I use the logarithmic returns on the S&P500 index minus inflation rates to measure real market returns and use the logarithmic returns on the S&P500 index minus one-month T-bill returns to measure market premiums.[13] In addition to patent shocks and R&D shocks, I include the following predictive variables in tests: Lagged market returns and premiums (Fama and French, 1988a), the dividend-price ratio "$d-p$" (Shiller, 1984; Campbell and Shiller, 1988; Fama and French, 1988b), the term spread "Term" and the default premium "Default" (Fama and French, 1989),

[12] A potential argument arises if investors perceive the autocorrelation ex ante. From a statistical perspective, Shephard and Harvey (1990) have shown that, in finite samples, it is difficult to differentiate a process including an autocorrelated component from an i.i.d. process. This point is taken by Bansal and Lundblad (2002) and Bansal and Yaron (2004).

[13] In unreported tables, I use the CRSP value-weighted index as the market portfolio and obtain almost identical testing results.

the relative bill rate "RRel" (Campbell, 1990, 1991), the dividend-earnings ratio "$d-e$" (Lamont, 1998), the aggregate consumption to wealth ratio "*cay*" (Lettau and Ludvigson, 2001), and the labor income to consumption ratio "SW" (Santos and Veronesi, 2006). The sources of all data considered are detailed in Appendix A.

In Table 1, I report the summary statistics of all variables and the correlation among patent shocks, R&D shocks, and other predictive variables. All descriptive statistics in Panel A are consistent with the literature. Moreover, I note that most predictive variables are highly autocorrelated. In fact, the first-order autocorrelations of patent shocks and R&D shocks (0.622 and 0.808, respectively) are lower than most other predictors in the literature. Panel B of Table 1 suggests the following: (1) the correlation between patent shocks and R&D shocks is 0.111; (2) both patent shocks and R&D shocks are positively correlated with contemporaneous S&P500 returns; and (3) neither shock is highly correlated with other predictors. The only exception is that R&D shocks are negatively correlated with Default (-0.657).

3.2 Testing results

I first examine the predictability hypothesis by regressing one-quarter ahead S&P500 real returns or excess returns on patent shocks or R&D shocks. According to the adjusted R-squares reported in Regressions 1 and 2 of Table 2, lagged patent shocks and R&D shocks are able to explain 8.5 and 7.6% of market returns, respectively. I also find that the coefficients of lagged patent shocks and R&D shocks are significantly positive at five percent level based on the t-statistics of Newey and West (1987) and Hodrick (1992), which confirm the market return predictability. In Regressions 3 and 4, I find that lagged patent shocks and R&D shocks explain 8.1 and 5.9% of market premiums, respectively. Moreover, the t-statistics of lagged technology shocks support the market premium predictability, despite the marginal Hodrick t-statistic in Regression 4.

I then standardize patent shocks and R&D shocks in regressions to inspect the economic significance of the predictability. In Regression 5, the estimated coefficient of standardized patent shocks is 2.3%, which implies the following: When this quarter's patent shock happens to be one standard deviation higher, the expected S&P500 return for the next quarter will increase by 2.3%.[14] On the other hand, Regression 6 indicates that one standard deviation rise in current R&D shock implies 2.2% increase in the expected S&P500 return for the next quarter. The coefficients of technology shocks in Regressions 7 and 8 are found to be of similar magnitude. As a result, the predictability of market returns and premiums based on technological innovations is of both statistic and economic significance. Note that, for interpretational purpose, I use only standardized technology shocks in the following text.

I then conduct pairwise horseraces in a multiple regression framework to compare patent shocks to other explanatory variables in predictive power. In Panel A of Table 3, I include each explanatory variable into the predictive regressions with technology shocks for S&P500 real returns. The upper part of Panel A reports that the coefficients of patent shocks remain significant and the corresponding Newey-West t-statistics are all above 3.0, much higher than those of other predictors.[15] In the lower part of Panel B, I find that the predictive ability of R&D shocks also remains significant with the existence of other predictors. Overall, Table 3 shows that technological innovations play a distinct role in explaining expected market returns.

Panel B of Table 3 reports the explanatory power of technology shocks and other predictors for market premiums. It shows that all t-statistics associated with patent shocks are above 3.0 and all t-statistics associated with R&D shocks (except one) are over 2.0. Since the statistical significance of both shocks is unaffected by the existence of other predictive variables, technological innovations therefore have unique explanatory power for expected market premiums as well. So far, all results provided in Tables 2 and 3 confirm that both market returns and premiums are predictable by technological innovations in a short horizon.

[14] I use *cay* as a benchmark and find that one standard deviation rise in *cay* implies 1.2% increase in the expected S&P500 return for the next quarter in the examined sample period.

[15] The Newey-West standard errors are adopted so that my testing results are comparable with recent papers in market return predictability (e.g., Lettau and Ludvigson, 2001; Rangvid, 2006; Liu and Zhang, 2008). Similar results are obtained in the addition of Term and Default and thus unreported.

Another noteworthy finding in Table 3 is that not all other predictors reveal predictive power in recent decades. In fact, only *cay* and RRel deliver reasonably significant coefficients in the examined sample period. This observation is not uncommon in the literature (e.g., Goyal and Welch, 2008) and may be attributed to the following factors: (1) U.S. economy has experienced some technology revolution waves since the 1970s, such as personal computers in the 1980s and the internet in the 1990s, which may cause mean shifts in states (e.g., Lettau and Van Nieuwerburgh, 2008); (2) the extreme market volatility in the 1990s may weaken most macroeconomic variables' explanatory abilities; or (3) the quarterly frequency setting in this study may be too short for some macroeconomic predictors to perform.

I further examine the predictability of market returns and premiums from a long-term forecasting perspective. Specifically, I regress cumulative market returns and premiums over the future k quarters on patent shocks and R&D shocks and make statistical inferences based on the Hodrick (1992) standard errors to account for overlapping errors.[16] Panel A of Table 4 demonstrates that patent shocks and R&D shocks are able to explain future 4-, 8-, and 12-quarter S&P500 real returns with reasonably high t-statistics and adjusted R-squares. For example, patent shocks that are one standard deviation higher raise quarterly expected market returns by 1.3% in subsequent four quarters (Regression 1). Panel B of the same table shows that patent shocks, but not R&D shocks, have significant explanatory power for long-term S&P500 excess returns. Nevertheless, all coefficients of R&D shocks remain positive. I also note that the t-statistics for R&D shocks decrease in horizon length k, which could be attributed to the relatively small sample size of R&D shocks. Overall, Table 4 points to a long lasting effect of technological innovations on expected market returns and premiums, and reaffirms earlier short-term forecasting results.

[16] Ang and Bekaert (2007) find that, in terms of size control, the Hodrick standard errors are much preferable than the Newey-West (1987) standard errors or the robust GMM generalization of Hansen and Hodrick (1980) in studying long-term return predictability. Moreover, I recognize Boudoukh, Richardson, and Whitelaw's (2008) concern about multi-horizon predictive regressions based on autocorrelated predictors.

3.3 Robustness checks

To check if the predictive power of technological innovations only exists in the internet era, I implement predictive regressions with patent shocks in the pre-internet period 1977Q1-1995Q4. In an unreported table, I find that patent shocks still significantly predict the real and excess returns on the S&P500 index with adjusted R-squares over five percent before the internet bubble.

An important econometric issue in predictive regressions is that the coefficients affiliated with persistent predictors are upward-biased, especially in small samples (e.g., Stambaugh, 1986, 1999).[17] In untabulated experiments, I consider the adjustments proposed by Stambaugh (1999) and Lewellen (2004) and obtain similar predictability findings, as the residuals of AR(1) models of patent shocks and R&D shocks do not explain the residuals of predictive regressions.

To examine if the predictability is driven by the small sample bias, I implement the test of Nelson and Kim (1993). I find that the bootstrap p-values of patent shocks in predicting market returns and premiums are 0.001 and 0.000, respectively. On the other hand, the bootstrap p-values of R&D shocks in forecasting market returns and premiums are 0.084 and 0.097, respectively.

Another considerable issue with predictive regressions is the influence of outliers in explanatory variables, which may create pseudo significant coefficients. I winsorize patent shocks and R&D shocks at five and ten percent (two-sided) and re-run predictive regressions. In untabulated results, I find that the statistical significance of winsorized technology shocks remains in the same level, and all adjusted R-squares are above five percent.

Lastly, I consider different specifications of technological innovations based on rolling AR(1) and eight-quarter moving averages. For the former, I run AR(1) for patent growth and R&D growth of four sequential quarters ($t-3$ to t) and make a prediction for the next quarter ($t+1$). After doing this for each four-quarter window, I obtain the time series of forecasting errors as proxies of patent shocks and R&D shocks. For the latter, I simply impose eight-quarter instead of

[17] On the other hand, Lewellen (2004) and Cochrane (2008) both comment that Stambaugh's estimation could substantially underestimate the predictability in short-term forecasting.

four-quarter in the procedure of Section 2.2. In the upper panel of Table 5, I find neither significant mean nor significant autocorrelation in the patent shocks and R&D shocks based on rolling AR(1). On the other hand, the patent shocks and R&D shocks based on eight-quarter moving averages are strongly autocorrelated with significantly positive and negative means, respectively.

Taking these two specifications into empirical testing, I still find empirical evidence for the predictability. In B.1 of Table 5, the coefficients associated with rolling AR(1) patent shocks are of statistical significance at five percent level, while the coefficients associated with rolling AR(1) R&D shocks are of statistical significance at ten percent level. The adjusted R-squares range from one to two percent. On the other hand, as reported in B.2, all coefficients associated with eight-quarter moving averages shocks are of statistical significance at five percent level and all adjusted R-squares are over four percent. These results suggest that the proposed predictability is fairly robust to the specification of technological innovations.

4 International evidence

In addition to the analysis of U.S. data, I investigate if the positive relation between technological innovations and market returns also exists internationally. Since patent data and R&D data are not always available in major countries, I have to conduct two separate experiments. In the first experiment, I inspect if China's patent shocks explain China's market returns. The patent data of European countries and Japan are not considered for two reasons: First, the prevailing coexistence of two patent systems in European countries (i.e., the European Patent Office and individual national patent offices) makes it extremely difficult to precisely measure one nation's total patent numbers. Second, the searchable patent databases of European countries and Japan are so different from USPTO databases that I have difficulty in obtaining comparable statistics.

In the second experiment, I examine if an individual country's R&D shocks explain domestic market returns using the data of Canada, France, Germany, India, Italy, Japan, and U.K. (G6 plus

India). As a result, my analysis covers many important countries. Among G7 and BRIC4 (Brazil, Russia, India, and China), only Brazil and Russia are not included because reliable statistics for Brazil's R&D expenses and Russia's GDP are not available.

4.1 The evidence from China

I use the returns on the MSCI China index (in local currency) as the proxy of market returns. The sample period starts from 1993Q1 due to data availability and the relatively short history of China's stock market.[18] The deposit rate and consumer price index are used to measure risk-free rate and inflation, respectively. The details of data sources are provided in Appendix B. For patent data, I collect the quarterly numbers of successful patent applications from the searchable patent database of the State Intellectual Property Office of China (SIPO), available since 1985Q1, as quarterly patent flows in China.[19] I accumulate quarterly patent flows to compute the patent growth and patent shocks in China using exactly the same procedure described in Section 2.

The top right panel of Fig. 3 illustrates both China's patent growth and patent shocks in 1993Q1–2007Q4. China's patent growth descends in the first half and then rises in the second half. On the other hand, the patent shocks represent a fairly stationary time series in both mean and volatility since 1994. The summary statistics of all variables are reported in Table 6. In Panel A of Table 7, I examine if patent shocks are able to explain expected market returns and premiums in China by regressing the real returns and excess returns of the MSCI China index on lagged patent shocks. The testing results are very significant. I find that patent shocks alone explain over 14% of the realized variation of market returns in terms of adjusted R-squares. In addition, the estimated coefficient 9.2% with t-statistic 3.08 suggests that one standard deviation rise in patent shocks increases expected market returns by over nine percent. Weaker but still significant results

[18]The modern China stock market started in 1992 as the Shanghai Stock Exchange was (re-)established in 1990 and the China Securities Regulatory Commission was established in 1992.

[19]http://www.sipo.gov.cn/sipo2008/zljs/. The searchable patent database of China is almost identical to USPTO databases, which makes it possible for me to obtain comparable statistics. Moreover, thanks to the relative independence of her patent system, China's patent statistics are more representative of country-specific, aggregate technology development.

are found in market premiums, in which patent shocks explain 3.1% of the realized variation of market premiums with an estimated coefficient 4.3% of t-statistic 2.06. The analysis of China's data not only confirms the technology-driven predictability of market returns and premiums but also corroborates the advantage of using patent data in empirical analysis.

4.2 The evidence from G6 plus India

Although international quarterly R&D expenditures are very difficult to collect, they can be estimated by quarterly GDP multiplied by the annual R&D to GDP ratios regularly reported by the Organisation for Economic Co-operation and Development (OECD) since 1981.[20] For each country, the base of cumulative R&D expenditures is calculated as accumulated historical GDP prior to 1981 multiplied by the R&D to GDP ratio in 1981. The only exception is India, which reports the R&D to GDP ratio and applicable GDP statistics only since 1990 and 1999, respectively. Following the procedure of Section 2, I accumulate each country's quarterly R&D flows to the corresponding base and obtain country-specific R&D growth and shocks. Note that these GDP-based R&D shocks are different from industry R&D shocks that I use in U.S. data. International stock market returns are collected from Datastream/Worldscope and the data of GDP, inflation, and risk-free rates are collected from the International Financial Statistics (IFS) of the International Monetary Fund (IMF). All data details are provided in Appendix B.

The summary statistics of market returns, inflation, risk-free rates, and R&D shocks of all seven countries are reported in Table 6. Note that not all countries' sample periods start in 1981 because their samples are restricted to the availability of market indexes. For example, the FTSE100 index began on 3 January, 1984. The time series of R&D growth and shocks of examined countries are plotted in Fig. 3. I note that all G6 countries' R&D shocks appear to be negative on average, while India's R&D shocks are positive in mean.

[20]OECD Factbook 2008: http://www.sourceoecd.org/rpsv/factbook/. Note that interpolation and extrapolation are used in the replacement of missing values in that data set.

I first run pooled predictive regressions by jointly regressing all countries' market returns or premiums on lagged, standardized R&D shocks with fixed effects. As reported in Panel B of Table 7, R&D shocks have significant predictive power for market returns and premiums as the associated t-statistics are 1.76 and 2.17, respectively, based on White's (1980) heteroskedasticity-consistent standard errors. According to the estimated coefficients, one standard deviation rise in country-specific R&D shocks increases expected market returns and premiums by 0.37% and 0.45% per quarter, respectively. I then run country-specific predictive regressions and find consistent results. The coefficients of R&D shocks are positive for all countries except France. Japan appears to be the country in which market returns and premiums are most positively correlated with R&D shocks as both t-statistics are over 2.5. Moreover, the stock markets of Germany and U.K. also react positively to R&D shocks with t-statistics around 1.0. The weakened predictability in country-specific regressions may be attributed to the relatively small sample size or idiosyncratic noises. Another reason could be that GDP-based R&D shocks include fundamental research expenses, so they are not as powerful as industry R&D shocks in explaining market returns. Overall, the empirical analysis of G6 plus India data reaffirms the technology-driven predictability.

5 Summary and interpretation

This paper documents the positive effect of aggregate technological innovations on expected market returns and premiums. Using patent data and R&D data, I first find that patent shocks and R&D shocks—that is, detrended patent growth and R&D growth—significantly predict the returns and premiums on the S&P500 index. More importantly, these two indicators present superior explanatory power against other macroeconomic and financial variables since the mid 1970s. From an international perspective, I find that country-specific patent shocks or R&D shocks significantly forecast the returns and premiums on stock indexes in several major countries. My empirical analysis therefore sheds light on the potentially important role of technological innovations in asset pricing.

The market return predictability presented in this study is consistent with the neoclassical q-theory literature. The most relevant research could be Lin (2007), which proposes a dynamic equilibrium model connecting endogenous technological progress to stock returns. He shows that firm-wise innovations increase expected stock returns by raising marginal product of capital and reducing the marginal cost of investment. So, when firms raise R&D input, their expected stock returns rise as well. In a broader scope, Chen and Zhang (2009) propose a model in which firms with higher expected profitability and lower investment cost provide higher expected stock returns. When the aforementioned arguments are extended to the aggregate scale, they imply a positive relation between technological innovations and expected market returns, as endogenous technological innovations are the main driving force for future productivity and efficiency. Nevertheless, the market premium predictability presented in this paper can not be explained by current works because they do not consider the risk free rate. Thus, further theoretical modeling for such an interesting relation is needed.

My predictability findings can also be related to the real option literature. Berk, Green, and Naik (2004) show that the required risk premiums for R&D ventures should be higher than traditional investments as the implicit leverage of compound options generates higher systematic risk. Li (2007) extends the above model and shows that, when financially constrained hi-tech firms raise R&D input, they become more vulnerable to systematic risk and provide higher risk premiums. I note that their arguments are based on systematic risk loadings. So, although these studies hint at a positive effect of technological innovations on expected stock premiums, their model implications may not directly apply to the aggregate relation.

Since my empirical investigation is motivated by the theoretical literature and empirical evidence at the firm level, it should not be regarded as a data snooping exercise (e.g., Sullivan, Timmermann, and White, 1999) or a set of spurious regressions (e.g., Ferson, Sarkissian, and Simin, 2003, 2008). Lastly, all predictability findings simply reflect the variation of expected market returns and premiums induced by time-varying technology shocks, so they do not conflict with the market efficiency hypothesis.

Appendices

Appendix A. The U.S. data in details

1. Market returns are measured by the returns on the S&P500 index and the CRSP value-weighted index; both are dividend-adjusted. The S&P500 index is from Yahoo Finance, while the CRSP value-weighted index is from Kenneth French's website.[21]

2. Inflation is based on the GDP implicit price deflator from Federal Reserve Economic Data (FRED).[22]

3. One-month Treasury bill (T-bill) returns of the Ibbotson Associates are from Kenneth French's website.

4. *cay* is available from Martin Lettau's website.[23] Note that the updated *cay* ends in 2006.

5. Labor income to consumption ratio (SW) is constructed following the calculation described in Santos and Veronesi (2006). The (aggregate) labor income is computed as: compensation of employees, received (Line 2) (= wage and salary disbursements + supplements to wages and salaries) + personal current transfer receipts (Line 16) - contributions for government social insurance (line 24) - personal current taxes (line 25).[24] All items are in National Income and Product Accounts (NIPA) Table 2.1: Personal Income and Its Disposition. All data series are from FRED.

6. Relative bill rate (RRel) is current one-month T-bill return minus the previous 4-quarter average.

7. Dividend-price ratio $(d - p)$ is available from Robert Shiller's website.[25]

8. Dividend-earnings ratio $(d - e)$ is available from Robert Shiller's website as well. Since the earnings data are not available after September 2007, I assume that the earnings in December 2007 remain on the same level as September 2007.

9. Term spread is 10-year government bond rate (constant maturity) minus 3-month T-bill rate (secondary market), both from FRED.

10. Default premium is Moody's BAA corporate bond rate minus AAA corporate bond rate, both from FRED.

[21] I thank Ken French for sharing the data at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[22] http://research.stlouisfed.org/fred2/.

[23] I thank Martin Lettau for making *cay* data available at http://pages.stern.nyu.edu/ mlettau/.

[24] The consumption defined here is the personal consumption expenditures on nondurable goods and services (lines 6 and 13) in Table 2.3.5 of NIPA: Personal Consumption. Labor income to consumption ratio is the labor income divided by consumption in each period. Accruals are neglected in this study.

[25] I acknowledge Robert Shiller for making the data available at http://www.econ.yale.edu/ shiller/data.htm.

Appendix B. The international data in details

1. Canada: Annual R&D to GDP ratios since 1981 are available from OECD Factbook 2008. Quarterly GDP (ID: L99BVnR@C156), consumer price index (CPI) (ID: L64@C156), and treasury bill rate (ID: L60C@C156) are from IFS. The market returns are computed based on the S&P/TSX60 index (1982Q2-2000Q4) and then the S&P/TSX Comp index (2001Q1-2007Q4), both from Datastream/Worldscope.

2. China: MSCI China index is obtained from Global Insight (ID: JL@CHIF). Note that these data are in daily frequency, and I compute quarterly returns as the growth rates of the index between the end dates of two quarters. Both quarterly deposit rate and CPI are from IFS (ID: L60L@C924 and L64nX@C924).

3. France: Annual R&D to GDP ratios since 1981 are available from OECD Factbook 2008. Quarterly GDP (ID: L99BnRnX@C132), CPI (ID: L64@C132), and three month treasury bill rate (ID: L60C@C132) are from IFS. The market returns are computed based on the CAC40 index (1989Q1-1990Q4) and then the SBF250 index (1991Q1-2007Q4), both from Datastream/Worldscope.

4. Germany: Annual R&D to GDP ratios since 1981 are available from OECD Factbook 2008. Quarterly GDP (ID: L99BVnR@C134), deflator index (ID: L99BInR@C134), and treasury bill rate (ID: L60C@C134) are from IFS. Note that I use GDP deflator because all available CPI data are discontinuous due to the reunion in 1990. The market returns are computed based on the DAX30 index from Datastream/Worldscope.

5. India: Annual R&D to GDP ratios since 1990 are available from OECD Factbook 2008. Quarterly GDP in factor costs (ID: GDPFCRNS@IN), CPI (ID: L64@C534), and commercial lending rate (ID: L60P@C534) are from IFS. Note that the quarterly GDP (measured by factor costs) is available only since 1999Q2. The market returns are computed based on the India BSE (SENSEX) 30 index from Datastream/Worldscope.

6. Italy: Annual R&D to GDP ratios since 1981 are available from OECD Factbook 2008. Quarterly GDP (ID: L99BnR@C136), CPI (ID: L64@C136), and treasury bill rate (ID: L60C@C136) are from IFS. The market returns are computed based on the Milan Mibtel index available since 1994Q2 from Datastream/Worldscope.

7. Japan: Annual R&D to GDP ratios since 1981 are available from OECD Factbook 2008. Quarterly GDP (ID: L99BnR@C158), CPI (ID: L64@C158), and discount rate (ID: L60@C158) are from IFS. The market returns are computed based on the Nikkei 225 (1985Q2-1990Q3) and then the Nikkei 500 (1990Q4-2007Q4), both from Datastream/Worldscope.

8. U.K.: Annual R&D to GDP ratios since 1981 are from OECD Factbook 2008. Quarterly GDP (ID: L99BnRnX@C112), CPI (ID: L64@C112), and treasury bill rate (ID: L60C@C112) are from IFS. The market returns are computed based on the FTSE100 index (1984Q3-1999Q4) and then the FTSE350 index (2000Q1-2007Q4), both from Datastream/Worldscope.

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Table 1: Summary statistics and correlations

Panel A reports the descriptive statistics of all variables, and Panel B reports selected contemporaneous correlations among patent shocks, R&D shocks, stock returns, and other predictors based on available data. The t-statistics reported are the results of t-tests for mean zero.

Panel A: Descriptive statistics								
	Mean (%)	Median (%)	Max. (%)	Min. (%)	Std. dev. (%)	t-stat. (zero)	1st order autocor.	Sample period
Market return, risk-free rate, and inflation								
S&P 500	2.414	2.467	20.867	-23.227	7.530	3.57	-0.007	1977Q1-2007Q4
1-M T-bill	1.475	1.332	3.453	0.222	0.740	22.20	0.944	1977Q1-2007Q4
Inflation	0.887	0.716	2.769	0.160	0.564	17.79	0.871	1976Q1-2007Q4
Technological growth and technology shocks								
r^{pat}	0.595	0.525	0.986	0.342	0.186	36.11	0.974	1976Q1-2007Q4
r^{rd}	1.423	1.427	1.677	1.076	0.139	83.66	0.937	1990Q2-2006Q4
$Tech^1$	0.009	0.007	0.085	-0.095	0.027	3.54	0.622	1977Q1-2007Q4
$Tech^2$	-0.014	-0.009	0.090	-0.125	0.048	-2.24	0.808	1991Q2-2006Q4
Other predictors								
cay	0.279	0.232	3.583	-3.622	1.427	2.18	0.880	1976Q1-2006Q4
SW	89.88	87.48	98.18	81.71	4.438	226.6	0.956	1976Q1-2007Q4
RRel	-0.007	-0.005	0.811	-0.955	0.320	-0.23	0.681	1976Q1-2007Q4
$d-p$	-359.9	-353.1	-277.9	-449.8	47.78	-85.05	0.986	1976Q1-2007Q4
$d-e$	-81.05	-84.91	-26.93	-119.0	22.09	-41.51	0.957	1976Q1-2007Q4
Term	1.671	1.723	3.800	-1.430	1.277	14.81	0.868	1976Q1-2007Q4
Default	1.065	0.928	2.513	0.560	0.416	28.93	0.904	1976Q1-2007Q4

Panel B: Correlations between technology shocks and other variables									
	$Tech^1$	S&P500	cay	SW	RRel	$d-p$	$d-e$	Term	Default
$Tech^1$	1.000	0.251	0.143	-0.230	0.168	-0.119	-0.255	0.000	-0.213
$Tech^2$	0.111	0.219	0.181	0.077	0.166	0.120	-0.112	-0.203	-0.657

Table 2: Patent shocks, R&D shocks, and S&P500 returns

This table reports the coefficients, t-statistics, and adjusted R-squares of the following predictive regressions: $r^s_{t+1} = const. + b\,Tech_t + u_{t+1}$ and $r^e_{t+1} = const. + b\,Tech_t + u_{t+1}$, where r^s denotes S&P500 real returns, r^e denotes S&P500 excess returns, $Tech_t$ denotes patent shocks ($Tech^1$) or R&D shocks ($Tech^2$), and u_{t+1} denotes residuals. In the lower panel, I standardize patent shocks and R&D shocks for interpretational purpose. The numbers in parentheses denote the t-statistics based on the Newey-West (1987) standard errors, and the numbers in brackets denote the t-statistics of Hodrick's (1992) 1B standard errors. Sample period: 1977Q1–2007Q4 for patent shocks and 1991Q2–2006Q4 for R&D shocks.

Shocks in original scale									
Real returns					Excess returns				
♯	$const.$	$Tech^1$	$Tech^2$	$adj R^2$	♯	$const.$	$Tech^1$	$Tech^2$	$adj R^2$
1	0.006	84.90		0.085	3	0.000	83.06		0.081
	(0.87)	(3.31)				(0.05)	(3.31)		
	[0.75]	[2.44]				[0.04]	[2.43]		
2	0.022		45.94	0.076	4	0.018		41.25	0.059
	(2.64)		(2.46)			(2.09)		(2.24)	
	[2.39]		[1.80]			[1.91]		[1.65]	
Standardized shocks									
Real returns					Excess returns				
♯	$const.$	$Tech^1$	$Tech^2$	$adj R^2$	♯	$const.$	$Tech^1$	$Tech^2$	$adj R^2$
5	0.014	0.023		0.085	7	0.008	0.023		0.081
	(2.26)	(3.31)				(1.28)	(3.31)		
	[1.95]	[2.44]				[1.07]	[2.43]		
6	0.016		0.022	0.076	8	0.012		0.020	0.059
	(1.83)		(2.46)			(1.37)		(2.24)	
	[1.74]		[1.80]			[1.31]		[1.65]	

Table 3: Pairwise horseraces in predicting S&P500 returns

I regress the real returns or excess returns on the S&P500 index at time $t+1$ on technology shocks and other predictors at time t. "Lag" denotes lagged S&P500 real or excess returns. The descriptions of all other predictive variables can be found in the text. Numbers in parentheses are the t-statistics of the Newey-West (1987) estimator, adjusted for serial correlation and heteroskedasticity. Sample period: 1977Q1–2007Q4 for patent shocks and 1991Q2–2006Q4 for R&D shocks. Note that both patent shocks ($Tech^1$) and R&D shocks ($Tech^2$) have been standardized for interpretational purpose. Numbers in boldface indicate p-values under 5% (one-sided).

Panel A: Predicting S&P500 real returns									**Panel B: Predicting S&P500 excess returns**								
Patent shocks									**Patent shocks**								
const.	Lag	$Tech^1$	*cay*	SW	RRel	$d-p$	$d-e$	$adjR^2$	*const.*	Lag	$Tech^1$	*cay*	SW	RRel	$d-p$	$d-e$	$adjR^2$
0.015	-0.080	**0.025**						0.083	0.008	-0.085	**0.024**						0.080
(2.34)	(-1.22)	(3.20)							(1.31)	(-1.29)	(3.21)						
0.012		**0.022**	**0.812**					0.102	0.006		**0.021**	**0.776**					0.095
(1.75)		(3.15)	(1.98)						(0.88)		(3.14)	(1.89)					
-0.033		**0.024**		0.052				0.078	-0.022		**0.023**		0.034				0.074
(-0.22)		(3.05)		(0.32)					(-0.15)		(3.04)		(0.21)				
0.014		**0.025**			**-3.503**			0.099	0.008		**0.025**			**-3.538**			0.096
(2.40)		(3.55)			(-2.31)				(1.36)		(3.53)			(-2.39)			
0.074		**0.024**				0.017		0.089	0.055		**0.023**				0.013		0.080
(1.38)		(3.34)				(1.11)			(1.02)		(3.30)				(0.86)		
0.034		**0.025**					0.025	0.082	0.027		**0.024**					0.024	0.078
(1.58)		(3.30)					(0.95)		(1.29)		(3.26)					(0.92)	
R&D shocks									**R&D shocks**								
const.	Lag	$Tech^2$	*cay*	SW	RRel	$d-p$	$d-e$	$adjR^2$	*const.*	Lag	$Tech^2$	*cay*	SW	RRel	$d-p$	$d-e$	$adjR^2$
0.018	-0.107	**0.024**						0.072	0.013	-0.108	**0.021**						0.055
(1.73)	(-0.99)	(2.55)							(1.31)	(-0.97)	(2.32)						
0.015		**0.020**	**0.768**					0.095	0.011		**0.018**	**0.769**					0.078
(1.58)		(2.13)	(1.85)						(1.14)		(1.90)	(1.81)					
-0.060		**0.022**		0.089				0.061	-0.161		**0.019**		0.202				0.046
(-0.12)		(2.35)		(0.15)					(-0.31)		(2.08)		(0.33)				
0.017		**0.020**			4.055			0.078	0.013		**0.018**			3.724			0.058
(1.91)		(2.69)			(1.32)				(1.44)		(2.42)			(1.19)			
0.201		**0.020**				0.046		0.098	**0.202**		**0.018**				0.048		0.084
(1.69)		(2.31)				(1.53)			(1.69)		(2.07)				(1.56)		
0.005		**0.022**					-0.013	0.063	0.003		**0.019**					-0.010	0.045
(0.21)		(2.57)					(-0.42)		(0.13)		(2.32)					(-0.34)	

Table 4: Patent shocks, R&D shocks, and S&P500 returns in the long run

I run the following multiple-horizon predictive regressions: $r^s_{t+k}+...+r^s_{t+1} = const.+b\,Tech^1_t$ (or $Tech^2_t$)$+u_{t+k,t}$ and $r^e_{t+k}+...+r^e_{t+1} = const.+b\,Tech^1_t$ (or $Tech^2_t$) $+ u_{t+k,t}$, where r^s denotes S&P500 real returns, r^e denotes S&P500 excess returns, k denotes the length of forecasting horizon, and $u_{t+k,t}$ denotes the overlapping residual. The sample periods involving patent shocks ($Tech^1$) and R&D shocks ($Tech^2$) are 1977Q1–2007Q4 and 1991Q2–2006Q4, respectively. Note that both patent shocks and R&D shocks have been standardized for interpretational purpose. Numbers in brackets are t-statistics based on the Hodrick (1992) 1B standard errors. The reported coefficients have been standardized by the number of quarters (k) to be comparable to one-quarter ahead predictive regressions.

Panel A: Real Returns					**Panel B: Excess Returns**				
$\sharp$	*const.*	$b\,(Tech^1)/k$	$b\,(Tech^2)/k$	$adjR^2$	$\sharp$	*const.*	$b\,(Tech^1)/k$	$b\,(Tech^2)/k$	$adjR^2$
4-Quarter					**4-Quarter**				
1	0.015	0.013		0.102	7	0.009	0.012		0.096
	[2.13]	[2.23]				[1.23]	[2.15]		
2	0.016		0.013	0.098	8	0.011		0.011	0.069
	[1.85]		[1.72]			[1.38]		[1.47]	
8-Quarter					**8-Quarter**				
3	0.015	0.008		0.082	9	0.009	0.008		0.077
	[2.13]	[1.96]				[1.23]	[1.85]		
4	0.015		0.010	0.076	10	0.011		0.007	0.036
	[1.65]		[1.88]			[1.23]		[1.26]	
12-Quarter					**12-Quarter**				
5	0.024	0.010		0.084	11	0.009	0.006		0.079
	[2.13]	[2.16]				[1.38]	[2.21]		
6	0.014		0.009	0.061	12	0.011		0.006	0.020
	[1.97]		[1.35]			[1.50]		[0.90]	

Table 5: The predictive abilities of other proxies of technological innovations

The upper panel reports the descriptive statistics of other technology shocks. The t-statistics reported are the results of t-tests for mean zero. In the lower panel, I run the following regressions: $r^s_{t+1} = const. + b\ Tech_t + u_{t+1}$ and $r^e_{t+1} = const. + b\ Tech_t + u_{t+1}$, where r^s denotes S&P500 real returns, r^e denotes S&P500 excess returns, $Tech_t$ denotes other technology shocks, and u_{t+1} denotes residuals. Note that all shocks used in regressions have been standardized for interpretational purpose. Numbers in parentheses are the t-statistics of the Newey-West (1987) estimator, adjusted for serial correlation and heteroskedasticity.

	Mean (%)	Median (%)	Max. (%)	Min. (%)	Std. dev. (%)	t-stat. (zero)	1st order autocor.	Sample period
A.1: Rolling AR(1)								
Patent	0.004	0.004	0.210	-0.112	0.034	1.42	0.093	1977Q2-2007Q4
R&D	-0.007	-0.006	0.091	-0.095	0.036	-1.43	0.030	1991Q3-2006Q4
A.2: Eight-quarter moving averages								
Patent	0.020	0.017	0.118	-0.040	0.030	7.05	0.753	1978Q1-2007Q4
R&D	-0.020	-0.018	0.117	-0.156	0.072	-2.14	0.901	1992Q2-2006Q4

B.1: Rolling AR(1)					**B.2: Eight-quarter moving averages**				
♯	*const.*	b (*Patent*)	b (*R&D*)	$adjR^2$	♯	*const.*	b (*Patent*)	b (*R&D*)	$adjR^2$
Real returns					Real returns				
1	0.014	0.012		0.015	5	0.015	0.016		0.046
	(2.02)	(2.22)				(2.23)	(2.70)		
2	0.015		0.014	0.018	6	0.016		0.020	0.070
	(1.56)		(1.47)			(1.69)		(2.14)	
Excess returns					Excess returns				
3	0.008	0.012		0.016	7	0.009	0.016		0.045
	(1.17)	(2.37)				(1.31)	(2.63)		
4	0.011		0.013	0.012	8	0.012		0.017	0.052
	(1.17)		(1.33)			(1.27)		(1.84)	

Table 6: Summary statistics: International data

This table reports the summary statistics of all variables considered in the empirical analysis of international data including Canada, China, France, Germany, India, Italy, Japan, and U.K. The t-statistics reported are the results of t-tests for mean zero.

	Variable	Mean (%)	Median (%)	Max. (%)	Min. (%)	Std. (%)	t-stat. (zero)	1st auto. autocor.
Canada	Market returns	2.66	2.49	23.53	-24.70	8.02	3.36	0.04
1982Q2-2007Q4	Inflation	0.73	0.70	3.06	-0.91	0.62	12.00	0.75
	Risk-free rate	1.64	1.40	3.87	0.50	0.84	19.89	0.96
	R&D shocks	-0.02	-0.02	0.10	-0.17	0.05	-5.34	0.60
China	Market returns	1.72	-0.40	80.87	-35.23	20.84	0.64	-0.13
1993Q1-2007Q4	Inflation	5.19	1.89	26.87	-2.05	7.59	5.29	0.97
	Risk-free rate	1.22	0.63	2.75	0.50	0.88	10.79	0.98
	Patent shocks	-0.08	-0.07	0.85	-0.76	0.27	-2.38	0.68
France	Market returns	2.83	3.39	29.85	-27.35	10.61	1.96	-0.04
1989Q1-2007Q4	Inflation	0.49	0.51	1.36	-0.23	0.35	13.35	0.87
	Risk-free rate	1.34	0.99	2.91	0.50	0.74	15.34	0.98
	R&D shocks	-0.06	-0.06	0.01	-0.16	0.04	-12.35	0.98
Germany	Market returns	3.35	4.80	35.11	-36.82	11.59	3.01	-0.04
1981Q3-2007Q4	Inflation	0.62	0.45	13.53	-0.43	1.36	4.70	0.20
	Risk-free rate	1.20	0.99	2.94	0.45	0.56	22.03	0.97
	R&D shocks	-0.02	-0.01	0.08	-0.09	0.03	-7.24	0.68
India	Market returns	4.61	6.35	31.12	-18.66	13.40	2.27	0.18
2000Q4-2007Q4	Inflation	1.12	0.98	2.80	-0.89	0.98	6.51	-0.02
	Risk-free rate	2.89	2.88	3.31	2.69	0.16	85.75	0.92
	R&D shocks	0.00	-0.02	0.13	-0.15	0.09	0.13	0.02
Italy	Market returns	2.57	1.36	46.28	-21.12	11.27	1.72	-0.00
1994Q2-2007Q4	Inflation	0.66	0.63	1.86	0.00	0.33	15.20	0.86
	Risk-free rate	1.23	1.00	2.78	0.50	0.70	13.34	0.97
	R&D shocks	-0.02	-0.02	0.03	-0.12	0.03	-4.94	0.71
Japan	Market returns	1.14	2.19	23.16	-34.30	11.02	0.99	0.11
1985Q2-2007Q4	Inflation	0.16	0.06	0.93	-0.34	0.31	4.97	0.97
	Risk-free rate	0.43	0.13	1.50	0.03	0.45	9.06	0.98
	R&D shocks	-0.04	-0.24	12.47	-17.89	4.22	-0.09	-0.29
U.K.	Market returns	2.48	3.45	18.97	-27.61	8.07	2.98	-0.02
1984Q3-2007Q4	Inflation	0.92	0.77	4.68	-0.67	0.82	10.87	0.43
	Risk-free rate	1.82	1.48	3.63	0.85	0.78	22.66	0.97
	R&D shocks	-0.01	-0.01	0.03	-0.07	0.02	-6.04	0.72

Table 7: Technology shocks and market returns: International data

In Panel A, I regress China's real market returns or premiums on standardized patent shocks. In Panel B, I regress the other seven country's real market returns or premiums on standardized, country-specific R&D shocks using both pooled regressions and country-specific regressions. In pooled regressions, I consider fixed effects for the intercept terms of individual countries and focus on the coefficient of standardized R&D shocks across all countries. In country-specific regressions, I regress each country's real market returns or premiums on standardized R&D shocks. $Tech_t$ denotes standardized patent shocks (China) or R&D shocks (G6 plus India). Numbers in brackets are the t-statistics based on White's (1980) heteroskedasticity-consistent standard errors for pooled regressions. Numbers in parentheses are the t-statistics of the Newey-West (1987) estimator, adjusted for serial correlation and heteroskedasticity. The sample includes Canada (1982Q2-2007Q4), China (1993Q1-2007Q4), France (1989Q1-2007Q4), Germany (1981Q3-2007Q4), India (2000Q4-2007Q4), Italy (1994Q2-2007Q4), Japan (1985Q2-2007Q4), and U.K. (1984Q3-2007Q4).

Panel A	**Real returns**			**Excess returns**		
	const.	*Tech*	$adjR^2$	*const.*	*Tech*	$adjR^2$
China	-0.068	0.092	0.141	-0.018	0.043	0.031
	(-2.54)	(3.08)		(-0.76)	(2.06)	

Panel B	**Real returns**						**Excess returns**					
	Pooled			*Country-specific*			*Pooled*			*Country-specific*		
Country	*Fixed*	*Tech*	$adjR^2$	*const.*	*Tech*	$adjR^2$	*Fixed*	*Tech*	$adjR^2$	*const.*	*Tech*	$adjR^2$
Canada	0.019	0.0037	0.00	0.019	0.0010	-0.01	0.010	0.0045	0.02	0.010	0.0001	-0.01
		[1.76]		(1.81)	(0.08)			[2.17]		(1.27)	(0.01)	
France	0.004			0.004	-0.0024	-0.01	0.010			0.010	-0.0024	-0.01
				(0.31)	(-0.20)					(0.83)	(-0.20)	
Germany	0.027			0.027	0.0103	-0.00	0.022			0.022	0.0107	-0.00
				(2.37)	(1.03)					(1.92)	(1.09)	
India	0.058			0.058	0.0028	-0.04	0.054			0.054	0.0100	-0.03
				(2.12)	(0.11)					(1.97)	(0.38)	
Italy	0.016			0.016	0.0054	-0.01	0.011			0.011	0.0070	-0.01
				(1.00)	(0.31)					(0.66)	(0.40)	
Japan	0.010			0.010	0.0138	0.01	0.007			0.007	0.0150	0.01
				(0.78)	(2.58)					(0.57)	(2.84)	
U.K.	0.000			0.000	0.0030	-0.00	-0.009			-0.009	0.0039	0.00
				(0.08)	(0.95)					(-2.62)	(1.28)	

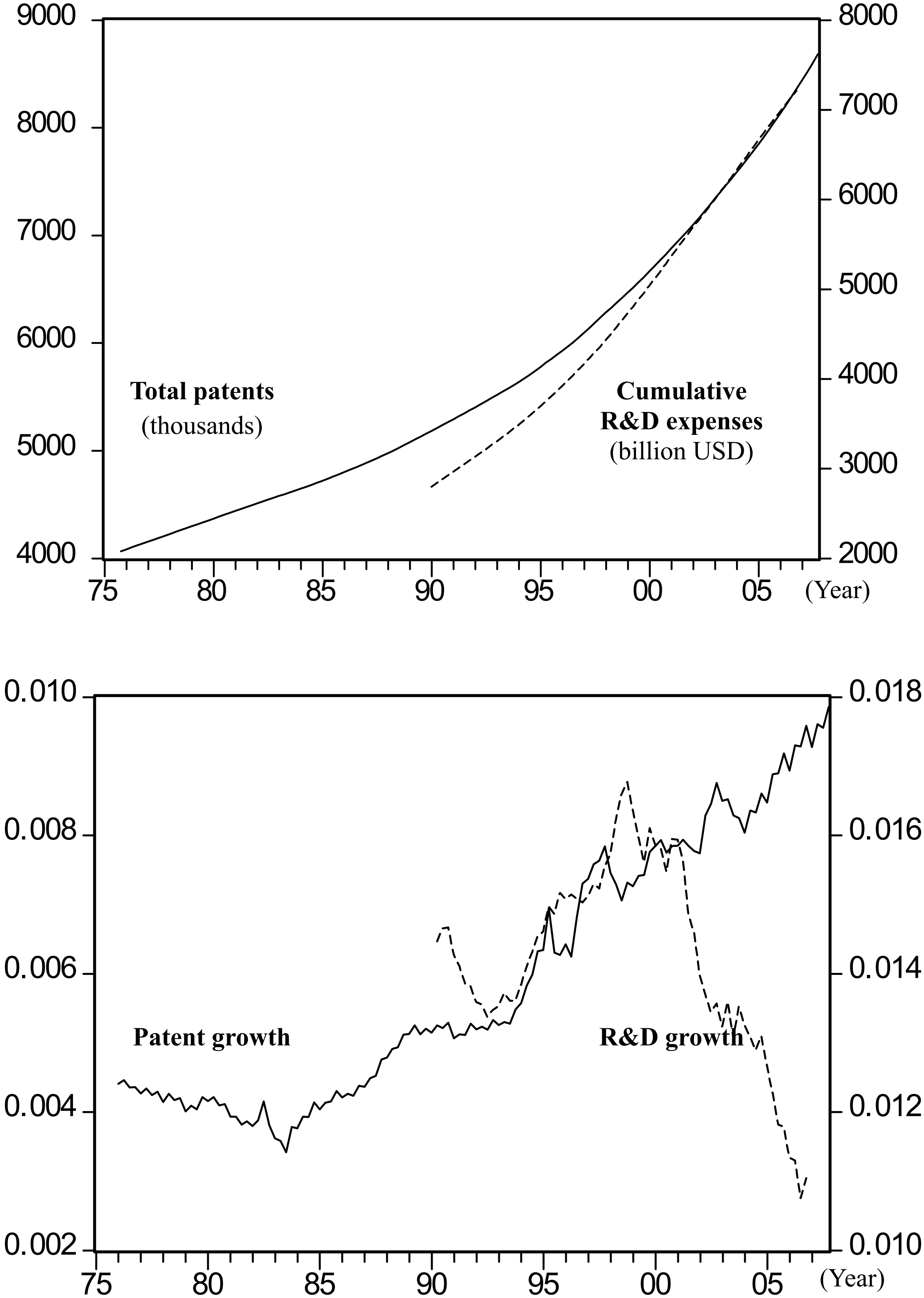

Fig. 1. The level and growth of U.S. patents and R&D expenses. The upper panel: The solid line denotes patent stock (the number of total successful patent applications in thousands) and the dashed line denotes R&D stock (the accumulation of real industry R&D expenses in billions of USD in 1996). The lower panel: The solid line denotes patent growth and the dotted line denotes R&D growth. In both panels, the left vertical axis is for patent data, and the right vertical axis is for R&D data. All details are provided in Section 2.1.

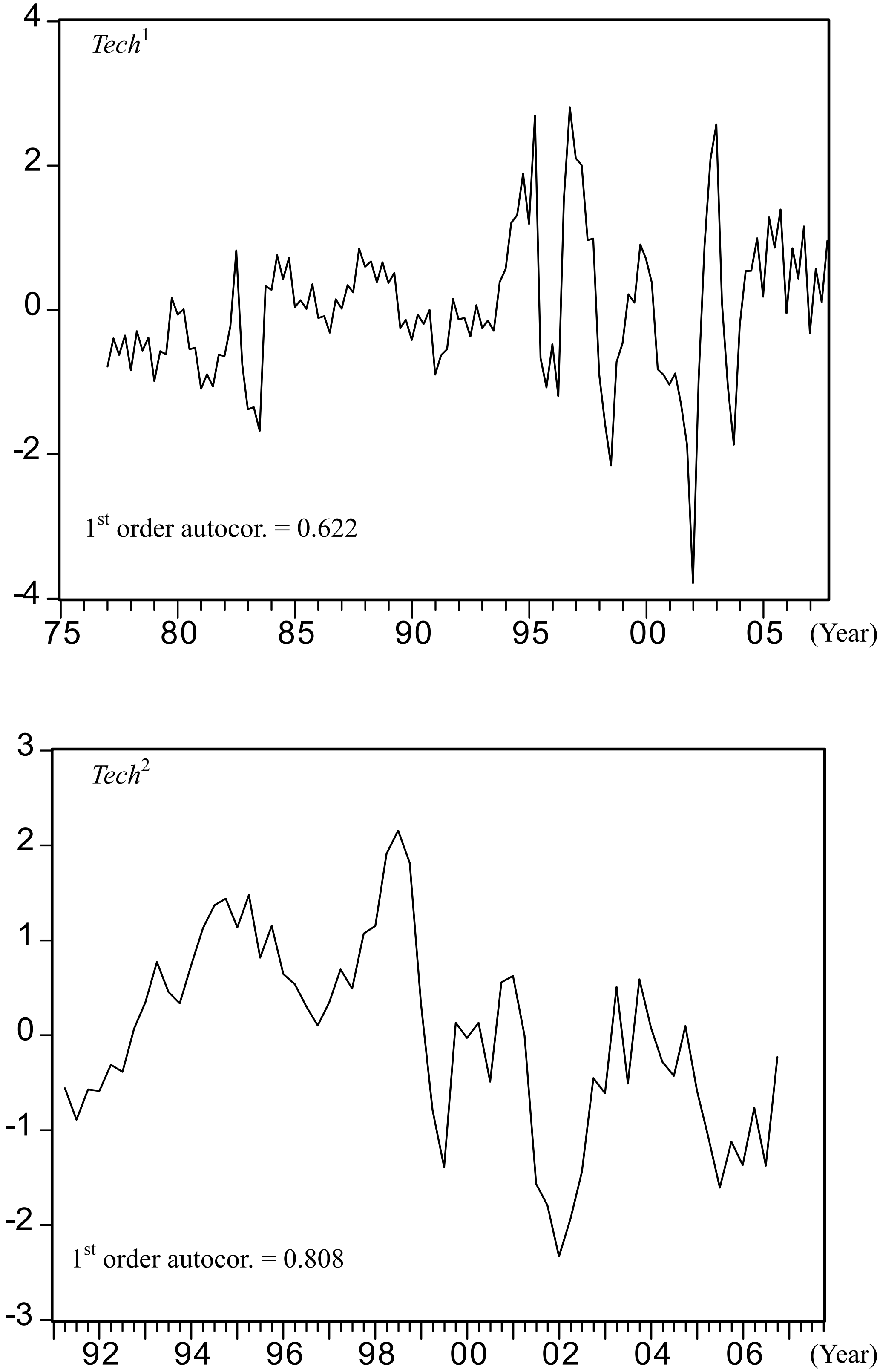

Fig. 2. Patent-based and R&D-based technology shocks. I plot the patent shocks ($Tech^1$) in the upper panel and the R&D shocks ($Tech^2$) in the lower panel. Note that these shocks have been standardized for interpretational purpose. Details are provided in Section 2.2.

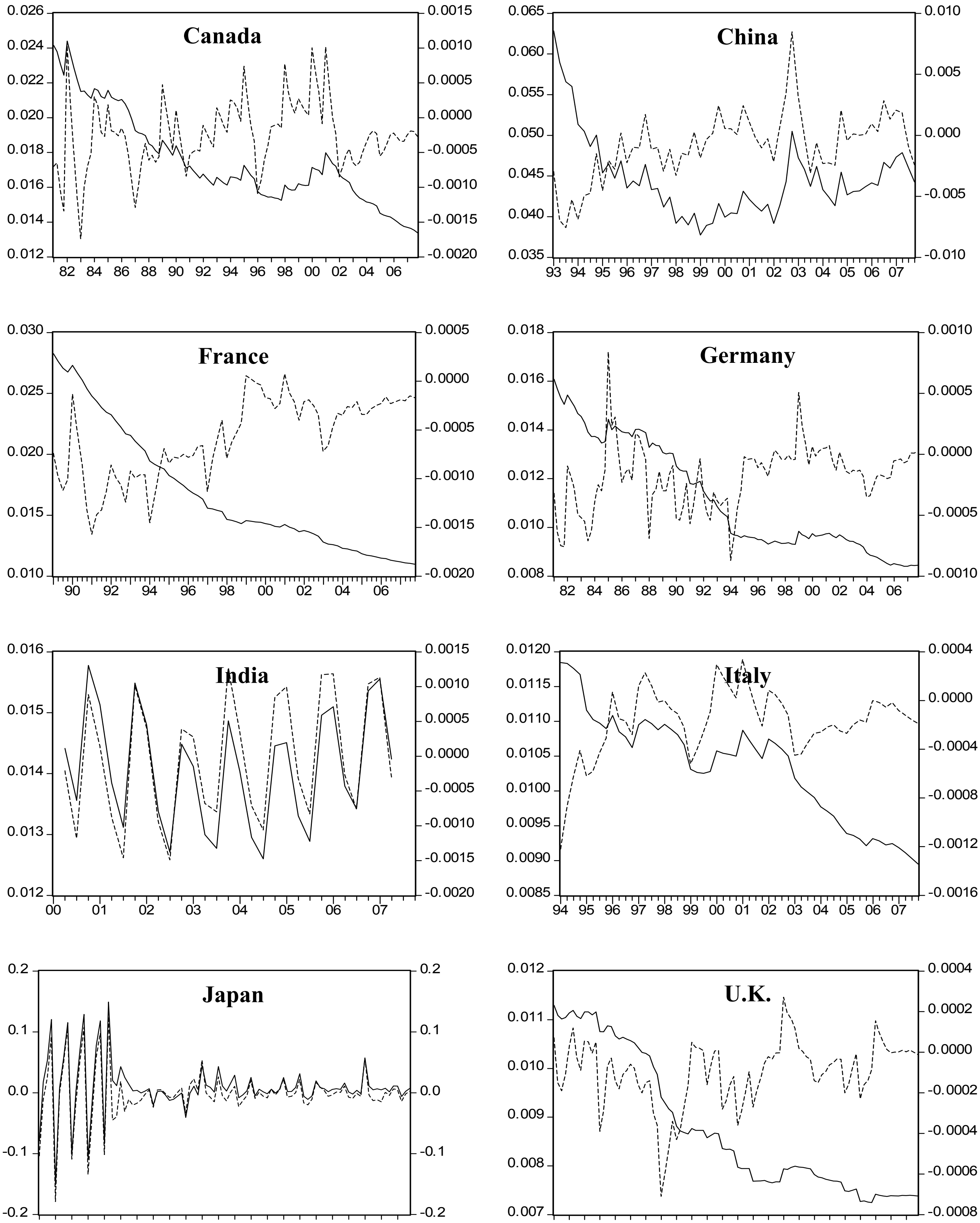

Fig. 3. International technological growth and shocks. This figure shows patent growth and patent shocks in China, and R&D growth and R&D shocks in G6 plus India. The solid line denotes the growth and the dashed line denotes the shocks. The left vertical axis is set for the growth, and the right vertical axis is set for the shocks. The horizontal axis is set for the year. Details are provided in Section 4.