Aggregate Technology Shocks and Market Return Predictability

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Abstract

This paper highlights the role of technology in asset pricing by demonstrating expected market return predictability based on aggregate technology shocks from both a theoretical and an empirical perspective. In a model economy context, I derive a general equilibrium solution, in which positive technology shocks imply higher expected market returns and market premium via productivity increase. This implication is strongly supported by empirical evidence in both the U.S. and U.K. I use the total patent growth and research and development (R&D) expenditure growth to measure aggregate technological growth, and find that both proxies have explanatory power for the growth of real gross domestic product (GDP). Most importantly, I confirm that the patent shocks and R&D shocks have strong predictive power for market returns and market premium.

JEL classification: E32; E44; G12; O30

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1 Introduction

The evidence of the economic impact of science and technology is all around us.
Zvi Griliches (1987)

Since the seminal paper of Solow (1957), the economic literature has long recognized that technologies, as observable activities that permanently improve the productivity, as a driving force behind economic growth. An ongoing testament to this argument is the advent of personal computers and internet, which in the past decade has undoubtedly reshaped the global economy and our lives. The relationship between technology and asset returns is, on the contrary, rarely discussed in the finance literature. In this study, I analyze this relationship from an aggregate perspective: I construct a one-firm general equilibrium model to explain the dynamics between aggregate production, aggregate stock price, and aggregate technology of the whole society.[1] This model answers why and how aggregate technology affects expected market portfolio returns in the time series. This study contributes to the literature by: (1) demonstrating that aggregate technology shocks, i.e. the unexpected aggregate technological growth, can explain the time series variation of expected market portfolio returns; and (2) proposing and verifying the total patent numbers and total R&D expenditures as two measurable proxies for aggregate technology level.

In the first part of this paper, I construct an abstract model economy composed of one good, one representative agent, and one representative firm. Despite its simplicity, this simple model describes the interactive dynamics among financial and labor markets, firm's productions, and representative agent's work and consumption choices. With a separable logarithmic utility function, I derive an explicit general equilibrium solution to this economy, which characterizes the stochastic discount factor and asset return in terms of technology shocks and non-technology shocks. The main implication is that technology shocks alter the time series of equilibrium investment returns, and thus imply commensurate changes in expected equity market returns and market premium.

The economic explanation for the predictability of market returns by technology shocks is relatively straightforward: The budget-constrained representative agent becomes more impatient because he observes the increase in representative firm's productivity due to a positive technology shock, which is of permanent income effect. This makes the agent prefer to consume more today and ask higher expected asset returns tomorrow. I can also explain the predictability through the production-side channel: If there occurs a positive technology shock, the productivity rises permanently. This make the budget-constrained firm's expected investment returns increase accordingly. Since the expected market returns are tied to expected investment returns in equilibrium, the expected market returns are higher. This return predictability does not, how-

[1] I then define "aggregate technology" as a measurable state variable that describes the effects of all up-to-date technologies on real output.

ever, contradict market efficiency. Rather, it simply reflects that technology shocks explain part of the time series variation of the stochastic discount factor and return expectations.

To confirm the proposed model and its predictions, I rely on empirical study that necessitates proxies for aggregate technological growth. I propose two proxies, total patent growth and total research and development (R&D) expenditure growth, which match the stated definition and widely used in the literature.[2] Unlike in previous studies, I have these two measurable and "pure" proxies for aggregate technological growth and shocks (unexpected growth), which allows me to confirm their impacts on real production and asset prices.

Data from the United States and the United Kingdom are considered in my empirical study. In the U.S. data, I first observe that patent and R&D expenditure growth explain gross domestic product (GDP) growth. I then find that shocks to U.S. patent growth and R&D growth can predict future Center for Research in Security Prices (CRSP) value-weighted index returns and excess returns and Standard and Poor's 500 (S&P500) index returns and excess returns. Furthermore, these two shocks compare favorably against other competing predictors including *cay*, labor income to consumption ratio, relative risk-free rate, dividend to price ratio, payout ratio, term spread, and default spread. The found predictability is of statistical and economic significance, and is robust to several robustness checks. Similar results are found in the U.K. data: British patent growth explains U.K. GDP growth, and British patent shocks predict future Financial Times Stock Exchange 100 (FTSE100) index returns. My investigation therefore provides strong empirical evidence for the proposed theoretical linkage between technology shocks and expected market returns.

This study relates to several streams of the literature. The first is the technology and asset returns literature. There are limited empirical studies exploring the relationship between asset returns and technological activities on the firm/industry level. The earliest study in this stream could be Pakes (1985), who investigates the dynamics among patents, R&D costs, and stock returns on a micro data set that contains 120 firms over an 8-year period, and finds that stock returns are correlated with concurrent and lagged patents and R&D expenses. Other studies in this direction focus mainly on connecting the cross-sectional variations of stock returns with firms' research activities: Chan, Lakonishok, and Sougiannis (2001), Arora, Ceccagnoli, and Cohen (2005), and Rossi (2005) examine the R&D and patent premium; Apedjinou and Vassalou (2004) consider the firm's innovations and its stock returns. On the other hand, even fewer studies are devoted to theoretical modeling of the linkage between technology and asset returns: Pastor and Veronesi (2005) construct a model explaining the technological revolution process, in which a new technology is an idiosyncratic risk in the beginning and may become a systematic risk once being widely adopted. Panageas and Yu's (2006) model explain why technology shocks lead

[2] Patents and R&D expenditures have been commonly used as proxies for technologies in the literature since Griliches (1984) and Pakes (1985). I recognize that some other proxies exist: the number of scientific journal articles (Price, 1963), the number of book published (Alexopoulos, 2006).

to business cycles and countercyclical market premium. In this study, I propose a distinct and testable model, which can be empirically justified by measurable technology proxies, i.e. both patents and R&D expenses.

Since technology is an important component in the production function, I utilize a production-based asset pricing model to establish a theoretical relationship between varying aggregate technology levels and asset prices. Since Cochrane (1991), there has been a surge of production-based asset pricing models in the literature. Most of these models are devoted to analyzing predictors of the cross-sectional variations of stock returns, for example the value and size premium (e.g., Cochrane, 1996; Gomes, Kogan, and Zhang, 2003; Zhang, 2005a). Recently, some researchers have started to notice the role of technology in production-based asset pricing research. For example, Belo (2005) models "technology" heterogeneity using heterogeneous production functions to explain the cross-sections of stock returns. It is also found that only a few studies in this stream try to explain the time series variation of stock returns (Balvers, Cosimano, and McDonald, 1990; Cochrane, 1991; Rodriguez, Restoy, and Pena, 2002; Balvers and Huang, 2006), and virtually all of them use industrial production as the explanatory variable. By constructing a general equilibrium model in which the expected market returns are characterized by production variables, I can explain why the time series variation of market returns can be attributed to technology shocks.

Another relevant literature is market return predictability. Researchers have proposed several macroeconomic variables and financial ratios to predict market returns, and their reasons are that these variables contain valuable information pertinent to time dependent fluctuations in expected market returns due to time-varying economic conditions and investors' preferences. Financial ratios including the dividend to price ratio (Shiller, 1984; Campbell and Shiller, 1988; Fama and French, 1988), the term spread and default spread (Fama and French, 1989), the book-to-market ratio (Kothari and Shanken, 1997), and payout ratio (Lamont, 1998) have been employed to predict stock returns. On the other hand, macroeconomic variables including the relative risk-free rate (Campbell, 1990 and 1991), industrial production (Balvers, Cosimano and McDonald, 1990; Chen, 1991), aggregate consumption to wealth ratio ("*cay*" of Lettau and Ludvigson, 2001), and labor income to consumption ratio (Santos and Veronesi, 2006) have also been constructed as predictors. Since technology shock is a critical component of productivity, it may also serve as an explanatory variable for expected stock returns in terms of time series variations.

The rest of the paper is organized as follows. In Section 2, I construct an economy and derive a closed-form solution. In Section 3, I describe my data and discuss my empirical findings as well as robustness checks. Section 4 concludes this paper. All details are left to Appendices.

2 The Economy

In this section, I construct an economy to describe the interactive dynamics among financial markets, production activities and consumption choices. My model setting is based on, but differs substantially from, Balvers, Cosimano, and McDonald (1990), and Balvers and Huang (2006). This economy contains one representative agent, one representative firm, and one consumption good. While this economy is a simple one, it delivers an intuitive and tractable general equilibrium solution. More specifically, I can characterize the stochastic discount factor and the general equilibrium asset returns in terms of production variables. Such a characterization allows me to demonstrate why and how technology shocks affect real production and asset returns.

I first describe the basic setting and timeline of my model. I then derive the stochastic discount factor, the investment return, the market return, and the risk-free rate. Finally, I discuss the empirical implications of the proposed model.

2.1 Basic settings

The infinitely lived representative agent maximizes her/his period t time-additive expected utility as follows

$$\underset{\{n_t,\, s_{t+1},\, b_{t+1}\}}{Max} \left\{ u(c_t, \bar{n} - n_t) + \sum_{\tau=1}^{\infty} \beta^{\tau} E_t \left[u(c_{t+\tau}, \bar{n} - n_{t+\tau}) \right] \right\} \tag{1}$$

$$s.t. \quad c_t + s_{t+1}\, p_t + b_{t+1} = s_t(p_t + d_t) + b_t(1 + r_t^f) + n_t w_t, \tag{2}$$

where β is a subjective discount rate, and $u(c_t, \bar{n}_t - n_t)$ characterizes the agent's periodic utility function. The latter depends on the agent's consumption c_t and leisure $\bar{n} - n_t$, where $\bar{n}$ denotes total available time units and n_t denotes the labor input. s_t denotes the fractional share of the stock of the representative firm held by the agent, and d_t denotes the dividend per share distributed by the firm. p_t denotes the competitively determined stock price in time t, while b_t is the loan or debt provided by the agent, which is presumed to be risk-free. r_t^f is the risk-free rate for the period $t-1$ to t. Lastly, n_t and w_t denote the labor input and the competitive real wage, respectively.

The representative firm is operated to maximize its stock price, the total value of all discounted future dividends. The firm's maximization objective in time t is

$$\underset{\{n_t,\, k_{t+1},\, b_{t+1}\}}{Max} \left\{ d_t + \sum_{\tau=1}^{\infty} E_t \left[\left(\prod_{i=t+1}^{t+\tau} m_i \right) d_{t+\tau} \right] \right\} \tag{3}$$

$$s.t. \;\; d_t = F(n_t, k_t, A_t, \varepsilon_t) - k_{t+1} + b_{t+1} - b_t(1 + r_t^f) - n_t w_t \geq 0 \tag{4}$$

$$F(n_t, k_t, A_t, \varepsilon_t) = \alpha_0 {n_t}^{\alpha_1} k_t^{\alpha_2} {A_t}^{\alpha_3} \varepsilon_t \tag{5}$$

$$A_t = A_{t-1}\gamma_t, \quad \gamma_t = \mu\, exp\,(\xi_t), \tag{6}$$

where m_{t+1} denotes the stochastic discount factor of the investor (i.e., the agent) from time t to time $t+1$:

$$m_{t+1} = \beta \frac{\partial u(c_{t+1}, \bar{n} - n_{t+1})/\partial c_{t+1}}{\partial u(c_t, \bar{n} - n_t)/\partial c_t}. \tag{7}$$

Equation (4) essentially defines the dividend in the context of the firm's period-to-period budget constraint: d_t denotes the dividend distributed to the agent in time t, which must be larger than or equal to zero. The firm uses its production output and new debt issuances to pay dividends and wages, implement new investment, and pay off old debt cum interest. The firm's production output, $F(n_t, k_t, A_t, \varepsilon_t)$, derives from a Cobb-Douglas production function that contains labor input n_t, capital input k_t, a technology component A_t, and a temporary non-technological shock ε_t in level.[3] For simplicity in notation, I use $F_t(\cdot)$ to replace $F(n_t, k_t, A_t, \varepsilon_t)$ hereafter. k_{t+1} is the output in period t reserved for investment in period $t+1$, which fully depreciates after being utilized in time $t+1$.[4] A_t denotes the period t accumulated technology level that is the compound of technological growth, γ_t, since time 0. I assume γ_t is determined by a stationary growth μ and an unexpected permanent technology shock in growth, ξ_t, which satisfies $E_{t-1}[exp\ (\xi_t)] = E[exp\ (\xi_t)] = 1$. I assume that ξ_t is normally distributed with mean ν_ξ and variance σ_ξ^2. The last term in the production function, ε_t, represents the unexpected non-technology shock that is i.i.d. and satisfies $E_{t-1}[\varepsilon_t] = E[\varepsilon_t] = 1$ and $\varepsilon_t \gg 0$ (non-negative output). It is intended to capture all other uncertainties (e.g., oil shocks, fiscal shocks, and weather disasters technology).[5] ε_t is independent of the technology shock xi_t and other contemporaneous variables. It can be observed that, in this model, the Solow residuals are separated into a technology component (A_t) and a non-technology component (ε_t).

Some details of the technology are worth mentioning: First, like most models in the literature, I assume the "neutrality" of technology (Solow, 1957; Griliches, 1988, p.287): Technology does not change the structure of production function. Second, the obsolescence rate of technology (i.e., the depreciation of technology) is a constant and is absorbed by the μ in this study.[6] Third, the technology level and technological growth are exogenous state variables and unaffected by labor and capital input in this model.[7]

[3]Inclusion of technology in a Cobb-Douglas production function is common in the literature (e.g., Griliches, 1988, p.247). Gomulka (1990, p.52) proposes a production function including a technology component with a power parameter.

[4]The full depreciation assumption may be strong but is not unreasonable: Taking the national income and product accounts (NIPA's) of 1991 as an example, the gross private domestic investment is 3,211 billion USD, Federal nondefense gross investment is 99 billion USD, and consumption of fixed capital amounts to 2,904 billion USD.

[5]Denison (1967) could be the earliest paper to treat the productivity shock and the technical (knowledge) progress as separate components. Many recent studies in real business cycle research employ shocks other than technology shocks to explain economic fluctuations (Rebelo, 2005).

[6]Pakes and Schankerman (1984a) set a constant obsolescence rate of technology is constant, while Abel (1984) set a stochastic one.

[7]Panageas and Yu (2006) also set an exogenous technological growth process. Some previous studies treat

Here I recapitulate the effective timing of production variables: capital/investment needs only one period to build up, new technology invented/discovered in this period can be used in the next period, and labor input can be instantaneously adjusted. There is only one good in this economy, all variables considered in this model are in real term (i.e., no inflation). Moreover, the main risk sources in this model are the technology shocks, ξ, and the non-technology shocks, ε.

Here I summarize the timeline of my model:

1. In the beginning of a period, time t, two shocks occur: an unexpected permanent technology shock, ξ_t, and a temporary non-technology shock, ε_t. Both shocks are observed by the agent and the firm.

2. At the end of period t, the equilibrium wage and labor, are decided by the interaction of agent's labor supply and firm's labor demand. The firm then executes its production plan. The firm's output, $F(t)$, is used to pay the total wage bill and the old debt at the risk-free interest rate. Finally, the firm issues new debt, if necessary, implements new investment k_{t+1}, and distributes the dividend d_t. At the same time, the agent receives the dividend d_t and labor income $n_t w_t$, decides how much to consume today c_t and how much to invest in stock s_{t+1} given the current market stock price p_t, and how much debt b_{t+1} to lend to the firm at the next period given the equilibrium risk-free rate. The agent's and the firm's decisions are known by each other, and both parties share the same expectations on technological and non-technological uncertainties.

2.2 A closed form solution

To initiate my analysis, I need to posit the agent's utility function. I consider the case in which the agent's utility function is logarithmic and additively separable in leisure and consumption:

$$u(c_t, \bar{n} - n_t) = \rho_1 \, ln(c_t) + \rho_2 \, ln(\bar{n} - n_t); \tag{8}$$

in this case the stochastic discount factor from time t to time $t+1$ is

$$m_{t+1} = \beta \, c_t / c_{t+1}. \tag{9}$$

The utility function is taken from Long and Plosser (1983) and Hansen (1985).

There exist explicit solutions for the optimal c_t and k_{t+1} policy functions: each is propositional to total output:

$$\begin{aligned} c_t &= q \, F_t(\cdot) \\ k_{t+1} &= (1-q) F_t(\cdot), \end{aligned}$$

technological progress as a result of R&D, and therefore an endogenous process in production, e.g., Pakes (1985) and Abel (1984). This model may accommodate an endogenous technology component as $A_t = \kappa_0 \, {n_t}^{\kappa_1} k_t^{\kappa_2} A_{t-1}$, and I leave this topic for future research.

where $0 < q < 1$. These two conditions are derived from the analogous social planning formulation of the model. This unique Pareto optimal allocation derived in a social planner's model must coincide with the corresponding competitive equilibrium, which can be regarded as its decentralized counterpart (Harris, 1987; Danthine and Donaldson, 2001). Details are provided in Appendix A.

The equilibrium wage w_t and labor n_t are jointly determined by the firm and the agent acting competitively. The firm's choice of labor input can be obtained by first order condition (FOC) of Equation (3) with respect to n_t:

$$\frac{\alpha_1 F_t(\cdot)}{n_t} = w_t, \tag{10}$$

which simply states that the marginal product of labor equals the wage. The agent's choice of labor given the wage rate can be solved by differentiating Equation (1) with respect to n_t, which implies

$$\begin{aligned} 0 &= u_c(c_t, \bar{n} - n_t)\frac{\partial c_t}{\partial n_t} + u_{\bar{n}-n_t}(c_t, \bar{n} - n_t) = \frac{1}{c_t}\left(s_t\frac{\partial d_t}{\partial n_t} + w_t\right) - \frac{\rho_2}{\bar{n} - n_t} \\ &= \frac{1}{q\,F_t(\cdot)}\left(s_t\frac{\alpha_1 F_t(\cdot)}{n_t} + (1 - s_t)w_t\right) - \frac{\rho_2}{\bar{n} - n_t} = \frac{\alpha_1}{q\,n_t} - \frac{\rho_2}{\bar{n} - n_t}. \end{aligned} \tag{11}$$

This FOC states that, at the optimum, the marginal utility of one unit of leisure should equal the marginal gain of giving up one unit of leisure, which includes wages from working and dividends from share-holding of the firm. I can therefore solve the labor input and wage as:

$$n_t = \alpha_1\bar{n}/(\rho_2 q + \alpha_1) \quad \text{and} \quad w_t = \alpha_0\alpha_1[\alpha_1\bar{n}/(\rho_2 q + \alpha_1)]^{\alpha_1 - 1} k_t^{\alpha_2} A_t^{\alpha_3}\varepsilon_t. \tag{12}$$

It is observed that the labor is a constant, which matches the social planner's problem (Appendix A), and the wage is determined by the investment, technology, and production uncertainty.

The firm's investment choice is solved by differentiating Equation (3) with respect to k_{t+1}, which is

$$E_t\left[m_{t+1}\frac{\alpha_2 F_{t+1}(\cdot)}{k_{t+1}}\right] = 1 \quad \forall\, t, \tag{13}$$

where $\alpha_2 F_{t+1}(\cdot)/k_{t+1}$ denotes the investment returns, and is labelled R^i_{t+1}. By imposing $c_t = q\,F_t(\cdot)$ and $k_{t+1} = (1-q)F_t(\cdot)$ into Equation (13), it can be found that $1 - q = \beta\alpha_2$ and thus

$$k_{t+1} = \beta\alpha_2 F_t(\cdot); \quad c_t = (1 - \beta\alpha_2)F_t(\cdot). \tag{14}$$

Here I assume the risk-free assets are in zero net supply, i.e., $\{b_t\}_{t=1}^{\infty} \equiv 0$.[8] Moreover, the dividend can be derived as

$$d_t = F_t(\cdot) - \beta\alpha_2 F_t(\cdot) - n_t w_t = (1 - \beta\alpha_2 - \alpha_1)F_t(\cdot), \tag{15}$$

[8] In fact, since the firm's investment k_{t+1} is always less than its output $F_t(\cdot)$ in this model, the representative firm does not need to borrow anything from the agent.

where $n_t w_t = \alpha_1 F_t$ has been shown in Equation (10).

The final piece of this general equilibrium model is the equilibrium stock price, which can be obtained by the FOC of agent's expected utility with respect to s_{t+1}:

$$0 = \frac{\partial \left\{ u(c_t, \bar{n} - n_t) + \sum_{\tau=1}^{\infty} \beta^{\tau} E_t \left[u(c_{t+\tau}, \bar{n} - n_{t+\tau}) \right] \right\}}{\partial s_{t+1}},$$
$$\text{where} \quad c_t + s_{t+1}\, p_t + b_{t+1} = s_t(p_t + d_t) + b_t(1 + r_t^f) + n_t w_t. \tag{16}$$

Note that the labor n_t is a constant now. Solving the above equation forward will lead to a common pricing formula:

$$p_t = \sum_{\tau=1}^{\infty} E_t \left[\left(\prod_{i=t+1}^{t+\tau} m_i \right) d_{t+\tau} \right]. \tag{17}$$

Taking the derived c_t, c_{t+1}, and d_{t+1} into Equation (17), the stock price is solved as:

$$p_t = E_t \sum_{h=1}^{\infty} \beta^h \frac{c_t}{c_{t+h}}\, d_{t+h} = \frac{\beta}{1-\beta}\, d_t. \tag{18}$$

Without loss of generality, I normalize the number of shares to one in each period (i.e., $\{s_t\}_{t=1}^{\infty} \equiv 1$). Substituting the stock price p_t and other variables derived in this section back Equation (2), the agent's budget constraint is satisfied, and so the market is cleared.

The stock returns, R_{t+1}^s, can be represented as

$$R_{t+1}^s = \frac{p_{t+1} + d_{t+1}}{p_t} = \frac{1}{\beta} \frac{d_{t+1}}{d_t} = \frac{1}{\beta} \frac{F_{t+1}(\cdot)}{F_t(\cdot)}. \tag{19}$$

It may be observed that the investment returns exactly equals the stock returns ($R_{t+1}^s = R_{t+1}^i$) period by period,[9] and the Euler's equation $E_t[R_{t+1}^s m_{t+1}] = 1$ holds for all periods. The equality between market return and investment return is consistent with production-based asset pricing literature (e.g., Cochrane, 1991; Restoy and Rockinger, 1994; Zhang, 2005b).

The stock returns can be further decomposed as follows:

$$\begin{aligned}
R_{t+1}^s = R_{t+1}^i &= \alpha_2 F_{t+1}(\cdot)/k_{t+1} \\
&= \alpha_0 \alpha_2 n_{t+1}^{\alpha_1} k_{t+1}^{\alpha_2 - 1} A_{t+1}^{\alpha_3} \varepsilon_{t+1} = \alpha_0 \alpha_2 [\alpha_1 \bar{n}/(\rho_2 q + \alpha_1)]^{\alpha_1} [\beta \alpha_2 F_t(\cdot)]^{\alpha_2 - 1} A_{t+1}^{\alpha_3} \varepsilon_{t+1} \\
&= \alpha_0 \alpha_2 [\alpha_1 \bar{n}/(\rho_2 q + \alpha_1)]^{\alpha_1 \alpha_2} (\beta \alpha_0 \alpha_2)^{\alpha_2 - 1} k_t^{\alpha_2(\alpha_2 - 1)} A_t^{\alpha_3(\alpha_2 - 1)} \varepsilon_t^{\alpha_2 - 1} A_{t+1}^{\alpha_3} \varepsilon_{t+1}. \\
&= \Theta k_t^{\alpha_2(\alpha_2 - 1)} A_t^{\alpha_2 \alpha_3} exp\,(\alpha_3 \xi_{t+1}) \varepsilon_t^{\alpha_2 - 1} \varepsilon_{t+1},
\end{aligned} \tag{20}$$

where $\Theta = \alpha_0 \alpha_2 [\alpha_1 \bar{n}/(\rho_2 q + \alpha_1)]^{\alpha_1 \alpha_2} (\beta \alpha_0 \alpha_2)^{\alpha_2 - 1} \mu^{\alpha_3}$. Since n_{t+1} is constant and k_{t+1} depends on production in time t, this equation actually inform that the stock returns are determined by the time series of technology shocks and non-technology shocks.

[9] Since $k_{t+1} = \beta \alpha_2 F_t(\cdot)$, then the firm's investment return $F_{t+1}(\cdot)/\beta F_t(\cdot) = \alpha_2 F_{t+1}(\cdot)/k_{t+1}$.

The risk-free asset returns, R^f_{t+1}, and excess returns, $R^s_{t+1} - R^f_{t+1}$, can be derived as follows

$$R^f_{t+1} = \frac{1}{E_t[m_{t+1}]} = \frac{1}{E_t[\beta F_t(\cdot)/F_{t+1}(\cdot)]} = \Theta k_t^{\alpha_2(\alpha_2-1)} A_t^{\alpha_2\alpha_3} \Xi_{t+1} \varepsilon_t^{\alpha_2-1}, \quad (21)$$

$$R^s_{t+1} - R^f_{t+1} = \Theta k_t^{\alpha_2(\alpha_2-1)} A_t^{\alpha_2\alpha_3} [exp\,(\alpha_3\xi_{t+1})\varepsilon_{t+1} - \Xi_{t+1}]\varepsilon_t^{\alpha_2-1}, \quad (22)$$

where $\Xi_{t+1} = E_t\left[exp\,(-\alpha_3\xi_{t+1})\varepsilon_{t+1}^{-1}\right]^{-1}$.

2.3 Model-implied predictability

Now I demonstrate that, by log-linearizing Equation (20), I can characterize the expected logarithmic stock return ($r^s_{t+1} = ln(R^s_{t+1})$) as follows:

$$r^s_{t+1} = constant + \alpha_2(\alpha_2 - 1)\, ln(k_t) + \alpha_2\alpha_3\, ln(A_t) + \alpha_3\xi_{t+1} \\ +(\alpha_2 - 1)\, ln(\varepsilon_t) + ln(\varepsilon_{t+1}). \quad (23)$$

Since this equation holds *ex post* and must also hold *ex ante* as well (e.g., Campbell and Shiller, 1988; Lettau and Ludvigson, 2001), I therefore formulate the expected logarithmic returns as follows:

$$E_t[r^s_{t+1}] = constant + \alpha_2(\alpha_2 - 1)\, ln(k_t) + \alpha_2\alpha_3\, ln(A_t) + \alpha_3 E_t[\xi_{t+1}] \\ +(\alpha_2 - 1)\, ln(\varepsilon_t) + E_t[ln(\varepsilon_{t+1})]. \quad (24)$$

Because $ln(A_t) = \sum_{\tau=0}^{t} ln(\gamma_\tau)$ and $\gamma_\tau = \mu\, exp\,(\xi_t)$, I can differentiate Equation (24) with respect to the technology shock ξ_t:

$$\frac{\partial E_t[r^s_{t+1}]}{\partial \xi_t} = \alpha_2\alpha_3 > 0, \quad (25)$$

because ξ_t is independent of k_t, ξ_{t-1}, ε_t, and ε_{t+1}. This equation implies that the technology shock, ξ_t, predicts future expected logarithmic stock return, $E_t[r^s_{t+1}]$.[10] Under rational expectations, the *ex ante* expected returns should equal mean *ex post*. In the empirical work, I can therefore regress the realized returns r^s_{t+1} on proxies of lagged technology shocks ξ_t and should obtain a positive coefficient with significance.[11] A example is provided below to illustrate the mechanism behind this predictability.

[10] Such an implied predictability is of short-term effect. Since α_2 is a small number, the h-step ahead predictability $\partial E_t[r^s_{t+1}]/\partial \xi_{t-h} = {\alpha_2}^h \alpha_3$ will diminish as h increases.

[11] I recognize that Elton (1999) states that the realized returns may not be an appropriate proxy for expected returns.

(Example) Here I use a simple case to exemplify the effect of one positive technology shock on future production and stock returns. I first make following assumptions: (1) the process of technology is set as

$$\{A_t\}_{t=1,...,T} = \{\underbrace{1, 1, 1, ..., 1}_{t=1,...,t^*-1}, \underbrace{1.5, 1.5, ..., 1.5}_{t=t^*,...,T}\},$$

which implies one half unit of shock occurring in time t^*; (2) the process of non-technology is of all ones: $\{\varepsilon_t\}_{t=1,...,T} \equiv 1$; (3) all variables decided before time t^* are in steady state, and are set as constants: F, $k = (1-q)F$, $c = qF$, and $R^s = 1/\beta$; (4) n is known to be constant in all time periods. Then, I start my economic dynamics with $F_{t^*}(\cdot)$:

$$F_{t^*}(\cdot) = \alpha_0 n^{\alpha_1} k^{\alpha_2} A_{t^*}^{\alpha_3} \varepsilon_{t^*} = \alpha_0 n^{\alpha_1} k^{\alpha_2} (1.5)^{\alpha_3} = (1.5)^{\alpha_3} F$$

$$k_{t^*+1} = (1-q) F_{t^*}(\cdot) = (1-q)(1.5)^{\alpha_3} F$$

$$c_{t^*} = q\, F_{t^*}(\cdot) = q(1.5)^{\alpha_3} F$$

$$d_{t^*} = (1 - \beta\alpha_2 - \alpha_1) F_{t^*}(\cdot) = (1 - \beta\alpha_2 - \alpha_1)(1.5)^{\alpha_3} F$$

$$F_{t^*+1}(\cdot) = \alpha_0 n^{\alpha_1} k_{t^*+1}^{\alpha_2} A_{t^*+1}^{\alpha_3} \varepsilon_{t^*+1} = F_{t^*}(\cdot) \left[\frac{k_{t^*+1}}{k_{t^*}}\right]^{\alpha_2} = F_{t^*}(\cdot)[(1.5)^{\alpha_3}]^{\alpha_2},$$

because $k_{t^*} = k$. The stock return in time $t^* + 1$ is

$$R^s_{t^*+1} = \frac{1}{\beta} \frac{F_{t^*+1}(\cdot)}{F_{t^*}(\cdot)} = \frac{1}{\beta}(1.5)^{\alpha_2\alpha_3} > R^s = \frac{1}{\beta},$$

and the stock return in time $t^* + 2$ can be easily derived as well:

$$R^s_{t^*+2} = \frac{1}{\beta} \frac{F_{t^*+2}(\cdot)}{F_{t^*+1}(\cdot)} = \frac{1}{\beta}(1.5)^{(\alpha_2)^2\alpha_3} > R^s = \frac{1}{\beta}.$$

The market premium in the next period is positively correlated with technology shocks:

$$\begin{aligned} \frac{\partial E_t[R^s_{t+1} - R^f_{t+1}]}{\partial \xi_t} &= \frac{\partial \Theta k_t^{\alpha_2(\alpha_2-1)} A_t^{\alpha_2\alpha_3} E_t[exp\,(\alpha_3\xi_{t+1})\varepsilon_{t+1} - \Xi_{t+1}]\varepsilon_t^{\alpha_2-1}}{\partial \xi_t} \\ &= \alpha_2\alpha_3 \Theta k_t^{\alpha_2(\alpha_2-1)} A_t^{\alpha_2\alpha_3} E_t[exp\,(\alpha_3\xi_{t+1})\varepsilon_{t+1} - \Xi_{t+1}]\varepsilon_t^{\alpha_2-1} > 0 \qquad (26) \end{aligned}$$

because (1) $A_t^{\alpha_2\alpha_3} = A_{t-1}^{\alpha_2\alpha_3} \mu^{\alpha_2\alpha_3} exp(\alpha_2\alpha_3\xi_t)$ and $\partial A_t^{\alpha_2\alpha_3}/\partial \xi_t = \alpha_2\alpha_3 A_t^{\alpha_2\alpha_3}$; (2) $exp(\alpha_3\xi_{t+1})\varepsilon_{t+1} > 0$ implies $E_t[exp\,(\alpha_3\xi_{t+1})\varepsilon_{t+1} - \Xi_{t+1}] > 0$ based on Jensen's inequality. So, a positive technology shock in time t implies higher market premium in time $t+1$.

It is also interesting to understand the formation of some common predictors in this model. The dividend to price ratio $(d - p)$, as shown in Equation (18), is a constant:

$$\frac{d_t}{p_t} = \frac{1-\beta}{\beta}.$$

Since the firm's earnings are $F_t(\cdot) - n_t w_t$ (no debt), the payout ratio $(d - e)$ is also a constant:

$$\frac{d_t}{F_t(\cdot) - n_t w_t} = \frac{(1 - \beta\alpha_2 - \alpha_1)F_t(\cdot)}{(1 - \alpha_1)F_t(\cdot)} = \frac{1 - \beta\alpha_2 - \alpha_1}{1 - \alpha_1}.$$

Finally, it turns out that the labor income to consumption ratio (SW) implied by this model is also a constant:

$$\frac{n_t w_t}{c_t} = \frac{\alpha_1 F_t(\cdot)}{(1 - \beta\alpha_2)F_t(\cdot)} = \frac{\alpha_1}{1 - \beta\alpha_2}.$$

As a result, in my simplistic model, the predictive power of $d - p$, $d - e$, and SW can not be explained.

2.4 GMM estimation

The closed-form solution derived in this model can be empirically tested using the generalized method of moments (GMM). I propose a testable joint hypothesis based on derivations shown in Sections 2.2 and 2.3:

$$\begin{aligned}
\text{Parameters}: &\quad 1 > \beta,\ 0 < \alpha_1,\ \alpha_2,\ \alpha_3 \\
\text{Production function}: &\quad 0 = E_t[\Delta F_{t+1} - (\Delta n_{t+1})^{\alpha_1}(\Delta k_{t+1})^{\alpha_2}\gamma_{t+1}^{\alpha_3}] && (27) \\
\text{Stock and investment returns}: &\quad 0 = E_t[R_{t+1}^s - \beta^{-1}\Delta F_{t+1}], && (28) \\
\text{Euler equation}: &\quad 0 = E_t[m_{t+1}R_{t+1}^s - 1] && (29) \\
\text{Predictability}: &\quad 0 = E_t[r_{t+1}^s - const - \alpha_2\alpha_3\xi_t] && (30)
\end{aligned}$$

where the stochastic discount factor $m_{t+1} = \beta(\Delta n_{t+1})^{-\alpha_1}(\Delta k_{t+1})^{-\alpha_2}\gamma_{t+1}^{-\alpha_3}(\Delta\varepsilon_{t+1})^{-1}$, and Δ denotes the gross growth rate (e.g., $\Delta n_{t+1} = n_{t+1}/n_t$). β, α_1, α_2, α_3, and *const* are free parameters (α_0 is not included because it is a scalar in the model). I use the U.S. data in 1977Q1–2004Q3 for GMM estimation: I use the growth of real GDP per capita for ΔF, growth of labor hours for Δn, growth of real capital per capita for Δk, patent growth γ^{pat} for γ, patent shocks ξ^{pat} for ξ, CRSP index returns for R^s, and ε are estimated based on following equation:

$$ln(\Delta F(n_t, k_t, A_t, \varepsilon_t)) = \alpha_1 ln(\Delta n_t) + \alpha_2 ln(\Delta k_t) + \alpha_3 ln(\gamma_t) + \epsilon_t. \quad (31)$$

Note that the details of data are described in Appendix B.

Equations (27) to (30) are exactly the moment conditions I can impose in GMM estimation, and their sample analogs are:

$$0 = \frac{1}{T}\sum_{t=1}^{T}\left[\left(\Delta F_{t+1} - (\Delta n_{t+1})^{\alpha_1}(\Delta k_{t+1})^{\alpha_2}\gamma_{t+1}^{\alpha_3}\right) z_t\right]$$

$$0 = \frac{1}{T}\sum_{t=1}^{T}\left[\left(R_{t+1}^{s} - \beta^{-1}\Delta F_{t+1}\right) z_t\right],$$

$$0 = \frac{1}{T}\sum_{t=1}^{T}\left[\left(m_{t+1}R_{t+1}^{s} - 1\right) z_t\right],$$

$$0 = \frac{1}{T}\sum_{t=1}^{T}\left[\left(r_{t+1}^{s} - const - \alpha_2\alpha_3\xi_t\right) z_t\right]$$

where z_t denotes the instrumental variables. I use the constant and the two-step-lagged time series of production growth and index returns as instrumental variables (i.e., $z_t = [1, \Delta F_{t-1}, R_{t-1}^{s}]$) because of the existence of ξ_t.[12] I use the standard two-step procedure to estimate the mean and standard deviations of parameters in my model, and calculate Hansen's J-test statistic (1982). To account for autocorrelation and heteroskedasticity of time series data, I use the Newey-West's (1987) covariance matrix estimate with lag number $nw = 4$ and 8 (note that the generally recommended lag number is 4, $floor(T^{1/3}) = 4$).

In Table 1, I show that all free parameters are of significance in lag 4 and 8: the estimated subjective discount factor β are 0.97 and 0.97, which are significantly lower than one; estimated α_1 (for labor) are 0.64 and 0.59, estimated α_2 (for capital) are 0.29 and 0.34, and estimated α_3 (for technology) are 0.62 and 0.54 – all are significantly larger than zero. The p-values of the J-test are 0.347 in lag 4 and 0.472 in lag 8, which imply that all moment conditions do not deviate much from zeros in GMM estimation. Therefore, the results obtained from GMM estimation and J-test indicate that Model 1 is appropriately specified and, most importantly, the model-impled predictability exists because α_2 and α_3 are confirmed to be significantly positive.

2.5 Economic interpretations

The economic reasoning behind technology's predictive power for asset returns can be explained in two ways and the first is based on the consumer's intertemporal substitution of consumption. By observing a positive technology shock occurring in time t, the agent knows that the productivity increases permanently. Such an increase in productivity, just like an increase in permanent income, makes the budget-constrained agent become more impatient and want to consume more today. As a result, the agent will ask higher expected asset returns in time $t+1$ in exchange for today's consumption. Such a relationship can be simply summarized by the equation $m_{t+1} = (R_{t+1}^{i})^{-1} = (R_{t+1}^{s})^{-1}$ implied by log-utility.

[12]Although the choice of instrumental variables may be arbitrarily, I considered other combinations of instrumental variables and obtained similar results.

The second explanation is based on the firm's investment returns. By observing a positive technology shock occurring in time t, the firm realizes that, given the fixed labor input, the firm's investment returns (precisely, the marginal product of capital) in time $t+1$ is higher.[13] Since the expected market returns should equal the expected investment returns, an increase in the latter should provoke an increase in the former.

It is tempting to assert that, by observing a positive technology shock, the agent would react by buying more stocks and hence pushing its price higher. This argument, however, presumes a fixed stochastic discount rate and unlimited endowment or borrowing, and both are not true in this economy. By linking $m_{t+1} = (R^s_{t+1})^{-1}$ and Equation (20) together, we know that a positive technology shock in t makes the agent prefer to consume more today under the budget constraint and thus require higher expected returns for holding a stock because the m_{t+1} is lower.[14] That can be interpreted as the stochastic discount effects exactly offset the cashflow effects, and implies no contradiction to the market efficiency hypothesis.

[13]The budget-constrained firm will increase its investment k_{t+1}, which decreases the marginal product of capital in time $t+1$ to some extent. However, the effect of a positive technology shock in time t will not be totally offset by the investment increase.

[14]The permanent shift-up in production function due to a positive technology shock is analogous to an increase in the agent's permanent income (Friedman, 1957).

3 Empirical Study: Data, Predictive Regression, and Robustness Check

In the previous section, I demonstrate that, within the model contexts, the aggregate technology shocks predict future expected stock returns. In this section, I examine whether these model implications are supported by real data in both the U.S. and U.K. I use the patent numbers and R&D expenditures to measure the technology levels, and derive technological growth and technology shocks.

3.1 Technology proxies and other data

All data used in this study are at the quarterly frequency.[15] Here I briefly describe the data used in my empirical study, and leave all details to the Appendix.

For the U.S. patent numbers, I use the U.S. patent applications data since 1976 that may be manually downloaded from the online database U.S. Patent Full-Text and Image Database (PatFT) of the U.S. Patent and Trademark Office (USPTO). As noted in Pakes (1985), these patent applications are "successful" patent applications since they are granted by USPTO sometime after being filed. Note that the successful patent application numbers are the only patent data set available before March 2001, and has been widely used in the literature of industry organization. Following Pakes (1985), I presume the effective dates of these issued patent applications in U.S. are their application dates. I use the successful patent application number by the end of time t to measure the technology level in time t.[16] To measure the technological growth, I need to have a base of the total number of all patents filed before 1976. I estimate the number based on Hall, Jaffe, and Trajtenberg's (2001) dataset; Since 1836, the total number of successful applications for U.S. patents amounts to $4,065,811$ ($= A_0^{pat}$) at the end of 1975. The time series of patent numbers are illustrated in the upper panel of Figure 1.

Some issues about using patents to measure technology are worth mentioning. First, although the level of patent applications may not match the aggregate technology level, their growth rates are presumed to be in a proportional relationship. Second, despite the heterogenous effects of patents, I use the argument of the "law of large numbers" (see Scherer (1965) and Griliches (1990)), and presume that all patent numbers are random variables from one distribution. Summing them up gives us the mean effect of all patents. Finally, I recognize one concern addressed by Jaffe and Lerner (2004) regarding the recent development of U.S. patent system. They report that the USPTO have approved many more patents since the early 1980s. I argue that the

[15]If I use annual data, the valid data of technology proxies can trace back only to the early 60s, which leaves us about forty sample points only.

[16]I recognize that Abel's (1984) comments on Pakes (1985) that state this is a strong assumption. However, I argue that some technology insiders, for example the patent law firms, can collect all qualified applications data to approximate the successful patent applications upon their filings and before they are eventually granted.

change in the U.S. patent system will not affect the validity of my empirical study because: First, the abnormal uptrend of patent growth, if any, will be removed in computing technology shocks because that I detrend the technological growth (illustrated in the lower panel of Figure 1) to compute technology shocks. I show that the time series of technology shocks is stationary as shown in Figure 2. Second, I consider another proxy (R&D expenses) and international evidence, both of which are immune to that patent anomaly.

For U.S. R&D expenditures, I sum up all quarterly R&D expenses (in millions of dollars) reported in the Compustat database and transform the number into 1996 dollars. A basis for the cumulative R&D expenditures to the end of 1988 is necessary to compute technological growth: I sum up the annual U.S. R&D expenditures in 1953-1988 reported in *National Patterns of Research and Development Resources:2003* of the National Science Foundation (2005) and obtain $3,299$ billion 1996 dollars ($= A_0^{rd}$) as the base level. Then, I add the quarterly total Compustat industry R&D expenditures to that base level, and get an approximate accumulative industry R&D expenditures. This approximation is reasonable because that, according to National Science Foundation (2005), industry R&D weights 71.9% of total U.S. R&D expenses during 1990-2000. The growth rate of this approximate accumulative industry R&D expenditures is named US R&D growth hereafter.[17] I check this constructed quarterly R&D growth with the NSF's national annual R&D growth, and find that they move consistently. The time series of R&D expenditures are illustrated in the upper panel of Figure 1.

Three issues about using R&D expenditures to measure technology are worth mentioning: First, although the input (R&D) may not fully become the output (technology), I hypothesize that the input-output ratio between R&D expenditures and the aggregate technology level is a constant. Second, I assume that the reported R&D expenses are optimal choices of firm managers following Bound et al. (1984), Pakes (1985), and others. Finally, it is well known that there exists a lag between the R&D input and technology output. Pakes and Schankerman (1984b) estimate that the mean lag is between 1.2 and 2.5 years, while this lag probably has become shorter in recent decades. I will accommodate this lag in constructing the proxy for the R&D-based technology shocks.

The U.S. patent growth (r_t^{pat}) and R&D growth (r_t^{rd}) are defined as follows:

$$r_t^{pat} = \frac{\text{Deseasonalized total patents by the end of time } t}{\text{Deseasonalized total patents by the end of time } t-1}$$

$$r_t^{rd} = \frac{\text{Deseasonalized cumulative real R\&D expenses by the end of time } t}{\text{Deseasonalized cumulative real R\&D expenses by the end of time } t-1},$$

where the deseasonalization method is a one-sided ratio to moving average-multiplicative method,[18]

[17] I assume that the accumulative industry R&D expenditures are steadily proportional to accumulative aggregate R&D expenditures.

[18] For series $\{y_t\}$ with seasonality, I first compute the moving average $x_t = (y_t + y_{t-1} + y_{t-2})/3$. Then let $r_t = y_t/x_t$, and compute $s_t = r_t/\sqrt[4]{r_t r_{t-1} r_{t-2} r_{t-3}}$. Finally, the seasonally adjusted y_t, $y_t^* = y_t/s_t$.

which does not to use future information in deseasonalization.

In the upper panel of Figure 1, I plot both the total patents in 1976Q1–2004Q3 and cumulative real R&D expenses in 1989Q1–2004Q3. It can be observed that these two series are smooth. In the lower panel of Figure 1, I plot the seasonally adjusted growth series of the two proxies for accumulative technology level. It is clear that these two growth series show significant co-movement: Both series increase in the 90s, reach their peaks around 1998, and then start to decline after that.

I then construct two proxies for the technology shocks based on r_t^{pat} and r_t^{rd}. The lower panel of Figure 1 demonstrates that both r_t^{pat} and r_t^{rd} contain stochastic trends. I employ a moving average detrending approach to disentangle the conditional expected growth and the unexpected shock.[19] I construct the first proxy for technology shocks based on patent growth ("patent shocks" hereafter) as follows:

$$\xi_t^{pat} = ln(r_t^{pat}) - \frac{1}{H}\sum_{h=1}^{H} ln(r_{t-h}^{pat}).$$

The second proxy for technology shocks is based on R&D growth ("R&D shocks" hereafter) and is constructed similarly as follows:

$$\xi_t^{rd} = ln(r_{t-1}^{rd}) - \frac{1}{H}\sum_{h=1}^{H} ln(r_{t-1-h}^{rd}),$$

where I impose one lag to accommodate the input-output lag in R&D activities.[20] The patent shock series ξ_t^{pat} and the R&D shock series ξ_t^{rd} are plotted in Figure 2. H is set to be four throughout this study.[21] Both shock series present stationarity without a significant trend, so the potential bias of an abnormal uptrend in patent growth proposed by Jaffe and Lerner (2004) no longer exists. Moreover, the autocorrelated ξ_t^{pat} and ξ_t^{rd} do not contradict the derivation of Equation (25).[22]

I use working hours as the labor input, real capital per capita as the capital input, and real GDP per capita as the production output. For the risk-free rate, I use the one-month Treasury Bill return. Several predictive variables are also considered in forecasting U.S. stock returns. They are "*cay*" of Lettau and Ludvigson (2001), labor income to consumption ratio "SW" of Santos and Veronesi (2006), dividend-price ratio "$d - p$" (Shiller, 1984; Campbell and Shiller, 1988; Fama and French, 1988), dividend-earnings ratio "$d - e$" ("payout ratio", Lamont, 1998), term

[19] This fitting is motivated by Campbell's fitting for relative risk-free rate (1990, 1991), which is also a smooth time series with stochastic trends. Moreover, this setting of expected growth is free of look-ahead bias.

[20] I recognize that one quarter lag is a simplistic setting and may not be appropriate for some sciences. However, I argue that the aggregate R&D input should start to affect aggregate technology level one period after.

[21] Results are robust to the selection of H: I have demonstrated similar results with $H = 8$ in an earlier version of this paper.

[22] The coefficient may change due to the autocorrelation, but is certainly positive.

spread "Term" and default premium "Default" (Fama and French, 1989), and relative riskless rate "RRel" (Campbell, 1991). Complete description of all U.S. data is provided in Appendix B.

In Table 2, I report all summary statistics of variables used in this study, and selected correlations between the technology shock proxies and other variables. Note that some variables are in logs while others are not. Numbers reported are consistent with recent studies (e.g., Lettau and Ludvigson, 2001; Santos and Veronesi, 2006). In the rightmost column of Panel A, I present the Augmented Dickey-Fuller (ADF) statistics (Dickey and Fuller, 1979; Said and Dickey, 1984) for all variables with first-order autocorrelation equal or larger than 0.85, and report corresponding critical values according to MacKinnon (1991).[23] It is found that all other predictors are very persistent except RRel, and only *cay* and the term spread reject the null hypothesis of the exist of a unit root according to the ADF test. The predictability results based on autocorrelated predictors call for advanced robustness checks. In the correlation reported in Panel B of Table 2, I report that ξ^{pat} and ξ^{rd} are not highly correlated with other predictors.

3.2 Predictive regressions

In this section, I run predictive regressions to further examine whether patent shocks and R&D shocks explain future expected market returns. I use logarithmic CRSP and S&P500 index simple returns and inflation-adjusted returns as proxies of market portfolio returns in logs. Since I get almost identical results in all index returns, I only report the results of logarithmic CRSP inflation-adjusted returns, which is referred as "CRSP index returns" hereafter. Moreover, I compare the explanatory/predictive power of technology shocks vis-a-vis other predictors at both short-term and long-term horizons.

In Table 3, I demonstrate that the patent shocks (ξ^{pat}) have significant predictive power for one-step ahead CRSP index returns. I consider both standardized patent shocks and original patent shocks as the predictors and find that, as the only regressor, their coefficients are all of significance. The t-statistics of regressions 1 and 8 are 3.37 and 3.38, respectively. The adjusted R^2s of regressions 1 and 8 are 0.05, which indicate that the patent shocks explain 5% of total variance of (realized) total stock market returns.

Then, I run pairwise horseraces in a multivariate regression framework to compare the predictive abilities of patent shocks and other predictive variables. Most predictor candidates proposed in previous studies are considered in the horseraces: consumption to wealth ratio (*cay*), labor income to consumption ratio (SW), relative short-term rate (RRel), log dividend to price ratio ($d-p$), log dividend to earnings ratio ($d-e$), term spread (Term) and default spread (Default).

[23]The lag number of models in computing ADF statistics are decided the model residuals' serial correlation, which should be zero. That is identified by Durbin-Watson statistics.

In all other regressions in Table 3, I find that the patent shocks' coefficients are of significance and have higher t-statistics than other predictors.[24] Note that, the results of these pairwise horseraces do not imply that patent shocks outperform other predictors. Instead, I interpret these results as evidence in support that the predictive power from technology shocks are distinct from other macroeconomic or financial ratio predictors'. The insignificance of other predictors could be attributed to one of the following reasons: some change in the economy's structure happens during 1976–2004 (e.g., the shift of mean in states mentioned in Lettau and Van Nieuwerburgh (2005)); the 1-quarter horizon is not long enough for those predictors to perform; their effects disappear in a relatively volatile period, e.g., the 90s; some predictors, for example the labor income to consumption ratio (SW), are used to predict market premium (excess returns) instead of market returns.

In Table 4, I report the results based on another proxy, the R&D shocks ξ^{rd}, which also show significant predictive power for one-step ahead CRSP index returns. The same as patent shocks, their coefficients in univariate predictive regressions are all of significance. The t-statistics of regressions 1 and 8 are 2.02 and 2.03, respectively. The adjusted R^2s of regressions 1 and 8 are 0.04, which indicate that the R&D shocks explain 4% of total variance of (realized) stock returns. In the pairwise horseraces, I also find that the R&D shock's coefficients are of significance (except regressions 5 and 12), while no other predictors have significant predictive ability. As a result, the model-implied market return predictability receives empirical support from patent and R&D data in the United States.

It is known that, in terms of predictability, the economic significance is as important as statistical significance. As reported in Tables 3 and 4, the coefficients of standardized ξ^{pat} and standardized ξ^{rd} are 0.02 and 0.03, respectively. Thus, a one standard deviation positive shock in patent shocks (R&D shocks) of this quarter implies a 2% (3%) increase in the expected market return in next quarter. Similar numbers can be obtained by original patent and R&D shocks multiplied by their standard deviations. Note that, in regression 5 of Table 3, a one standard deviation decrease in RRel implies a 1.15% increase in the expected market returns in next quarter ($-3.49 \times 0.326\%$). So, it is fair to state that the effect of technology shock on stock returns is of economic significance and reasonable magnitudes.

In Figure 4, I exemplify technology shocks' predictive ability by plotting the realized CRSP index returns and the forecasted returns (the first regressions in Tables 3 and 4). It is observed that the technology shocks, especially in the 90s, can capture the trend of market returns. Not surprisingly, the forecasted return series is quite smooth because that it aims to track the expected market returns, not the realized market returns.

I then consider the predictability in longer horizons by regressing the cumulative future market returns on technology shock proxies. Specifically, I consider Hodrick's (1992) 1B standard errors

[24] Results of Term and Default are both insignificant and unreported due to the space limit.

to account for the overlapping errors existing in cumulative returns so to draw more correct inference.[25] As reported in Table , the patent shocks and R&D shocks maintain their predictive power throughout 4-, 8-, and 12-quarter horizons and produces commensurate adjusted R^2. It is also found that the intercept terms are consistently positive with significance.

Now, I consider the technology shock's predictive power for the market premium based on predictive regression.[26] For the market premium, I consider inflation-adjusted CRSP excess returns and logarithmic excess returns, inflation-adjusted S&P 500 excess returns and logarithmic excess returns. Since similar results are found in four cases, I report only the result of the inflation-adjusted CRSP logarithmic excess returns case (CRSP excess returns hereafter). In Table 6, I demonstrate that both standardized patent shocks and R&D shocks provide significant predictive power for one-step ahead CRSP excess returns. The adjusted R^2s of regressions 1 and 8 are 0.05 and 0.03, which indicate that the patent shocks (R&D shocks) explain 5% (3%) of total variance of (realized) excess returns. So, technology shocks' predictive power is of economic significance, and coefficients reported here are very close to those in Table (3) for market returns. I then consider the long-term performance of these two predictors. As reported in Table , the patent shocks and R&D shocks maintain their predictive power throughout 4-, 8-, and 12-quarter horizons and produces reasonable adjusted R^2. I note that, unlike what found in market return predictability, the intercept terms are all insignificant.

Based on all these findings, I conclude that the technology shock proxies, ξ^{pat} and ξ^{rd}, can contribute to explaining expected future market returns and market premium. Moreover, technology shocks have predictive power which differs from that of other macroeconomic variables and financial ratios in forecasting market returns and market premium, based on horserace regressions and pairwise correlations reported in the summary statistics table. Finally, this return predictability found in empirical study is consistent with my theoretical model. It does not arise from pure data snooping. Some additional robustness checks are provided in the following section.

3.3 Robustness checks

Perhaps the most intriguing question is whether the predictability based on technology shocks is a special consequence of the internet boom and burst period. To answer this question, I examine their predictability in the subsample 1977Q1-1995Q4 and report the results in Table 8. It can be observed that the patent shocks, ξ^{pat}, still predict CRSP index returns, and the coefficients of significance are close to the whole sample results. It would be ideal if we could check this predictability with data prior 1970. However, due to the unavoidable limitation in

[25] Ang and Bekaert (2006) study the long-term return predictability and conclude that the performance of Hodrick's 1B standard errors is much better than the Newey-West (1987) standard errors or the robust GMM generalization of Hansen and Hodrick (1980).

[26] I recognized that the magnitude of correlation implied in my model is in fact time variant.

data availability, all researchers cannot obtain appropriate technology proxies before 1970 (e.g., Chan, Lakonishok, and Sougiannis, 2001; Rossi, 2005). Another noteworthy finding from this Table 8 is that both *cay* and RRel are found to have significant predictive power, which may be explained by: (1) there is fundamental changes in the economy during 1976–2004; or (2) the predictive power of *cay* and RRel is diluted in the volatile period, e.g., the 90s. Regarding the insignificance of SW found, I suspect that the quarterly frequency may be inappropriate for the labor income to consumption ratio.

I recognize that the "reporting lag" (Balvers, Cosimano, and McDonald, 1990) is an important issue in predictability. Since most macroeconomic and financial ratio predictors are not immediately available at the end of a period, the relevant information is not fully revealed to the market (even insiders) in the beginning of the next period. To take this concern into account, I impose one more lag and run two-step ahead predictive regressions in patent shocks case.[27] In Table 9, I obtain results very close to Table 3. In R&D shocks case, the results in Table 4 have included one quarter for the input-output lag. Therefore, accommodating this possible reporting lag does not alter the conclusion that the technology shocks forecast market returns.

An important econometric issue in predictive regression is that the coefficients affiliated to autocorrelated predictors are upward-biased, especially in the small sample (e.g., Stambaugh, 1986, 1999).[28] In Table (10), I report that the bias based on Stambaugh's (1999) estimation and its effect on coefficient estimates. It is found that, although the patent shocks and R&D shocks are autocorrelated, their innovations (residuals of AR(1) model) do not correlated with the predictive regression's residuals (c_1 are not significant in Panel C). As a result, the possible small sample bias are negligible and does not alter the conclusion of predictability.

Boudoukh, Richardson, and Whitelaw (2005) address one concern about long-term predictability based on autocorrelated predictors: the multi-horizon predictive regressions are almost perfectly correlated with short-term predictive regressions. Their concern is less relevant to this empirical study because: First, my theoretical model, stated as Equations (24) and (25), mainly states short-term predictability. Therefore, instead of claiming long-term predictability, I regard the significant results found in long-term predictive regressions as supportive evidence for my short-term predictability. Second, both U.S. patent shocks and R&D shocks are less autocorrelated than most other predictors, so it is less likely that their long-term predictability is simply a replication of their short-term predictability.

[27] I argue that one quarter is long enough for the market, or at least insiders (e.g., large patent law firms or USPTO staff), to adjust the stock prices according to the technology shocks.

[28] On the other hand, Lewellen (2004) and Cochrane (2006) both comment that Stambaugh's estimation may substantially understate the predictability in short-term forecasting.

4 International evidence: U.K.

In this section, I inspect: (1) whether British patent data help to explain the pattern of real U.K. output better; and (2) whether U.K. technology shocks measured from patent data has explanatory power for expected U.K. stock returns.

I manually collect the British patent applications from the *Patents and Designs Journal* published weekly by the Patent Office of the United Kingdom.[29] I can therefore construct the time series of British patent growth and U.K. technology shocks using a procedure similar to that used in U.S. patent case. By the end of 1989, the total number of applications filed for British patent since 1948 amounted to $1,878,250$ according to the data provided by the U.K. Patent Office. Thus I can compute the British patent growth r_t^{UKpat}, and British technology shocks ξ_t^{UKpat} using a procedure identical to that used in U.S. data. For the market returns, I use the FTSE 100 index returns provided by Yahoo!Finance.[30] In Figure 3, I plot both the British patent application growth and the British patent shocks in 1991Q1–2004Q4. It is reasonable to conclude that the British patent shock series represents a stationary time series. The descriptions of all other macro-variables including the inflation, labor input (working hour), real capital input per capita, and real output (GDP) per capita are left to Appendix C.

First, to examine the relationship between technological growth and real output growth, I regress the logarithmic growth of real GDP per worker on logarithmic growth rates of labor hours, real investment per worker, and technology. As mentioned, I use the British patent growth rates to measure technological growth. In Table 11, I show that the real GDP per capita can be better explained with U.K. technological growth. The regression in Panel A delivers adjusted R^2 0.189, while the regression in Panel B delivers adjusted R^2 0.081 only. Meanwhile, the coefficient of technological growth in Panel A has statistical significance. I thus confirm that British patent data is a reasonable proxy for technology in general and better explains U.K. output dynamics.

In Table 12, I run short-term and long-term predictive regression to examine whether British technology shocks predict future FTSE100 index returns in logs. In the short-term predictability reported in Panel A, I show that standardized British patent shocks predict future FTSE100 index returns with significance, while the lagged FTSE100 index returns do not carry any predictive power. The coefficients of ξ^{UKpat} are 0.021 and 0.023 in regression 1 and 3, and these numbers are close to the coefficients found in the U.S. data. In Figure 5, I plot the actual returns and the fitted returns based on regression 1 of Table 12. It is observed that the predicted expected stock return matches the trend of realized stock returns and, not surprisingly, the predicted return series is less volatile than the realized one because I propose the predictability in expected market returns.

[29] Note that the number is total British patent applications, not successful patent applications. Nevertheless, this is the only available measure of U.K. patent accumulations in quarter.

[30] http://finance.yahoo.com

Finally, I inspect the predictability at longer horizons and report the results in Panel B of Table 12. I regress the cumulative future FTSE100 index returns in logs on the British patent shock, and find no significant predictability in 4-, 8-, and 12-quarter horizons according to Hodrick 1B method (1992). I therefore conclude that, different from the findings in U.S. data, patent shocks do not carry predictive power for long-term U.K. stock returns.

5 Conclusions

As a main driving force of economic growth, technology has been recognized as an influential factor in aggregate production. Does technology have something to do with finance, especially asset pricing? In this study, I analyze this question with both a theoretical model and empirical evidence. This study has novelties in both theoretical and empirical perspectives: I construct an economy that solves the dynamics of consumption, production, labor market, and financial assets in a general equilibrium framework. My model characterizes an aggregate technology component in the production function, in which I demonstrate that an unexpected positive technology shock raises expected investment returns and asset returns. The intuition of this model implication is that, since today's positive technology shock raises the firm's productivity, the agent's permanent income increases and becomes more impatient. This makes the agent require higher expected investment/asset returns in exchange for today's consumption.

In my empirical study, I first demonstrate that the technological growth can explain real production growth in both the U.S. and U.K. Then, I show that U.S. technology shocks, measured by U.S. patent shocks and R&D shocks, predict future CRSP index returns and S&P500 index returns at both long- and short-term horizons. More surprisingly, they outperform other predictors including *cay*, labor income to consumption, relative risk-free rate, dividend to price ratio, payout ratio, default premium, and term spread. I demonstrate that these two technology shocks also predict future CRSP excess returns and S&P500 excess returns at both long- and short-term horizons. Furthermore, it is found that the British patent shocks also forecasts future FTSE100 index returns. The proposed theoretical linkage between technology shocks and expected market returns is therefore strongly supported by empirical evidence. In addition, these findings suggest the potential of production-side variables in capturing time variant information regarding market expectation.

Possible future research directions include developing an equilibrium model with heterogeneous firms and technology shocks to explain cross-sectional variation of industry portfolio returns. The framework of this study can also be used to explain the unusual market return volatility during the internet era as a function of instability in technological growth. Third, I plan to derive the technology risk premium, which among other things may allow me to reexamine the underperformance of new issues from a different perspective.

Appendices

A. The social planer's problem

Because the unique Pareto optimal allocation proposed by a central planner model must coincide with the outcome of a competitive equilibrium model, I can solve the planning version of the model described in Section 2.3 and derive the equilibrium consumption and labor policy functions. They will then be imposed into the decentralized version of model in Section 2.3, which allows me to solve all other variables.

I assume there is a single, infinitely lived representative agent (consumer-worker-investor) whose problem is to maximize her/his time-additive expected utility in time t as follows

$$\max_{c_t, n_t}\{u(c_t, \bar{n} - n_t) + \sum_{\tau=1}^{\infty} \beta^{\tau} E_t \left[u(c_{t+\tau}, \bar{n} - n_{t+\tau})\right]\} \tag{32}$$

$$\begin{aligned} s.t.\ \ & c_t = F_t(n_t, k_t, A_t, \epsilon_t) - k_{t+1}, \\ & F(n_t, k_t, A_t, \epsilon_t) = \alpha_0 {n_t}^{\alpha_1} k_t^{\alpha_2} {A_t}^{\alpha_3} \varepsilon_t \\ & A_t = A_{t-1}\gamma_t, \quad \gamma_\tau = \mu exp\,(\xi_t), \end{aligned}$$

where β is a subjective discount rate ($0 < \beta < 1$), and $u(c_t, \bar{n}_t - n_t)$ characterizes the agent's period utility function that depends on the agent's consumption c_t and leisure $\bar{n} - n_t$ in time t; n_t denotes the labor input and $\bar{n}$ denotes total available time. k_{t+1} is the investment reserved for capital stock in the next period, which fully depreciates in production in time $t + 1$. The firm's production function, $F(n_t, k_t, A_t, \epsilon_t)$, follows a Cobb-Douglas form that contains labor input n_t, capital input k_t, a technology component A_t, and a non-technology production shock ε_t. For notational simplicity, I use $F_t(\cdot)$ instead of $F(n_t, k_t, A_t, \epsilon_t)$ hereafter. I assume that $0 < \alpha_1, \alpha_2, \alpha_3 < 1$. A_t denotes the technology level at time t that is the compound of technological growth, γ_t, since time 0. Since technological growth is persistent across time, I assume it follows a logarithmic random walk process with mean μ and an unexpected permanent technology shock in growth, ξ, which satisfies $E_{t-1}[exp\,(\xi_t)] = 1$ and ξ is normally distributed with mean ν_ξ and variance σ^2_ξ. The last term in the production function, ε_t, represents the unexpected temporary non-technology shock in level that is i.i.d. and satisfies $E_{t-1}[\varepsilon_t] = 1$ and $E_{t-1}[ln(\varepsilon_t)] = \nu_\varepsilon$, which accommodates all other uncertainties and is independent of the technology shock and other contemporaneous variables. There is only one good in this economy, and it is perishable so that the agent can only consume it today or invest it for tomorrow's production. In each time t, the agent first observes the technology shock and non-technology shock, and then decides the consumption, investment, and working time based on expectations for the future.

The agent's utility function is assumed to follow

$$u(c_t, \bar{n} - n_t) = \rho_1\, ln(c_t) + \rho_2\, ln(\bar{n} - n_t), \tag{33}$$

where ρ_1 and ρ_2 are strictly positive. The value function corresponds to problem in Equation (32) is as follows:

$$V(k_t, A_{t-1}, \xi_t, \varepsilon_t) = \max_{c_t, n_t}\{\rho_1 ln(c_t) + \rho_2 ln(\bar{n} - n_t) + \beta E_t[V(k_{t+1}, A_t, \xi_{t+1}, \varepsilon_{t+1})]\}. \quad (34)$$

Note that: (1) the state variable arguments of $V(\cdot)$ represent all information known to the agent in making her/his labor, consumption, and investment allocation decisions: capital stock, preceding technology level, current technological shock, and current non-technology shock. (2) I set $c_t = q_t F_t(\cdot)$, where q_t is the fraction of output to be consumed in time t, and therefore $k_{t+1} = (1 - q_t)F_t(\cdot)$.

I conjecture the solution is of the following value function form:

$$V(k_t, A_{t-1}, \xi_t, \varepsilon_t) = \phi_1 + \phi_2 ln(k_t) + \phi_3 ln(A_{t-1}) + \phi_4 \xi_t + \phi_5 ln(\varepsilon_t), \quad (35)$$

which is solvable and has an explicit unique solution.[31] By taking expectation of Equation (35), we know that

$$\begin{aligned} E_t[V(k_{t+1}, A_t, \xi_{t+1}, \varepsilon_{t+1})] &= E_t\{\phi_1 + \phi_2\, ln(k_{t+1}) + \phi_3\, ln(A_t) + \phi_4\, \xi_{t+1} + \phi_5\, ln(\varepsilon_{t+1})\} \\ &= \phi_1 + \phi_2\, ln((1 - q_t)F_t(\cdot)) + \phi_3\, ln(A_t) + \phi_4 E_t[\xi_{t+1}] + \phi_5 E_t[ln(\varepsilon_{t+1})] \\ &= \phi_1 + \phi_2\, ln(1 - q_t) + \phi_2\, ln(F_t(\cdot)) + \phi_3\, ln(A_t) + \phi_4\, \nu_\xi + \phi_5\, \nu_\varepsilon, \end{aligned}$$

because $ln(\gamma_{t+1}) = ln(\mu) + \xi_{t+1}$, $E_t[\xi_{t+1}] = \nu_\xi$, and $E_t[ln(\varepsilon_{t+1})] = \nu_\varepsilon$.

I then rewrite the maximization problem in Equation (34) as:

$$V(k_t, A_{t-1}, \xi_t, \varepsilon_t) = \max_{q_t, n_t}\{\rho_1 ln(q_t F_t(\cdot)) + \rho_2 ln(\bar{n} - n_t) + \beta E_t[V(k_{t+1}, A_t, \xi_{t+1}, \varepsilon_{t+1})]\}, \quad (36)$$

which can be derived as:

$$\begin{aligned} V(k_t, A_{t-1}, \xi_t, \varepsilon_t) = \max_{q_t, n_t}\{&\rho_1 ln(q_t) + \rho_1 ln(F_t(\cdot)) + \rho_2 ln(\bar{n} - n_t) \\ &+\beta\left[\phi_1 + \phi_2\, ln(1 - q_t) + \phi_2\, ln(F_t(\cdot)) + \phi_3\, ln(A_t) + \phi_4\, \nu_\xi + \phi_5\, \nu_\varepsilon\right]\}. \quad (37) \end{aligned}$$

Since the value function in the right hand side is concave with respect to n_t and q_t, I can use the FOCs to find the maximum. Because $ln(F_t(\cdot)) = ln(\alpha_0) + \alpha_1 ln(n_t) + \alpha_2 ln(k_t) + \alpha_3 ln(A_t) + ln(\varepsilon_t)$, the FOC with respect to n_t is

$$\begin{aligned} 0 &= \rho_1 \frac{\partial\, ln(F_t(\cdot))}{\partial\, n_t} - \frac{\rho_2}{\bar{n} - n_t} + \beta\phi_2 \frac{\partial\, ln(F_t(\cdot))}{\partial n_t} \\ &= \frac{\rho_1 \alpha_1}{n_t} - \frac{\rho_2}{\bar{n} - n_t} + \frac{\beta\phi_2\alpha_1}{n_t} \\ \text{So,} \quad n_t &= \frac{\alpha_1(\rho_1 + \beta\phi_2)\bar{n}}{\rho_2 + \alpha_1(\rho_1 + \beta\phi_2)}. \end{aligned}$$

[31] I benefited from a discussion with Jack Favilukis in solving this equation.

Also, the FOC with respect to q_t is

$$0 = \frac{\rho_1}{q_t} - \frac{\beta\phi_2}{1-q_t}.$$
$$\text{So,} \quad q_t = \frac{\rho_1}{\rho_1 + \beta\phi_2}.$$

Taking form (35), n_t, and q_t into Equation (37), I can solve for other parameters:

$$\begin{aligned}\phi_1 + \phi_2 ln(k_t) + \phi_3 ln(A_{t-1}) + \phi_4 \xi_t + \phi_5 ln(\varepsilon_t) &= \rho_1 ln(q_t) + \rho_1 ln(F_t(\cdot)) + \rho_2 ln(\bar{n} - n_t) \\ &+\beta\left[\phi_1 + \phi_2\, ln(1-q_t) + \phi_2\, ln(F_t(\cdot)) + \phi_3\, ln(A_t) + \phi_4\, \nu_\xi + \phi_5\, \nu_\varepsilon\right]. \quad (38)\end{aligned}$$

The right hand side can be further expanded by decomposing $ln(F_t(\cdot)) = ln(\alpha_0) + \alpha_1 ln(n_t) + \alpha_2 ln(k_t) + \alpha_3 ln(A_t) + ln(\varepsilon_t)$:

$$\begin{aligned}&\rho_1 ln(q_t) + \rho_1 ln(\alpha_0) + \rho_1\alpha_1 ln(n_t) + \rho_1\alpha_2 ln(k_t) + \rho_1\alpha_3 ln(A_t) + \rho_1 ln(\varepsilon_t) + \rho_2 ln(\bar{n} - n_t) \\ &+\beta\phi_1 + \beta\phi_2 ln(1-q_t) + \beta\phi_2 ln(\alpha_0) + \beta\phi_2\alpha_1 ln(n_t) + \beta\phi_2\alpha_2 ln(k_t) + \beta\phi_2\alpha_3 ln(A_t) + \beta\phi_2 ln(\varepsilon_t) + \beta\phi_3 ln(A_t) \\ &+\beta\phi_3 ln(\mu) + \beta\phi_4\nu_\xi + \beta\phi_5\nu_\varepsilon \qquad (39)\end{aligned}$$

By matching the coefficient of each variable in the left hand side of Equation (38) to those in the right hand side shown in Equation (39), I can solve all parameters for this planner's version. I note that the change of $ln(k_t)$ is independent of other state variables, which implies that the coefficients in both sides must match:

$$\phi_2 = \rho_1\alpha_2 + \beta\phi_2\alpha_2,$$
$$\text{which implies } \phi_2 = \frac{\rho_1\alpha_2}{1-\beta\alpha_2} > 0.$$

It is noted that ϕ_2 is a constant. Similarly, for $ln(\varepsilon_t)$,

$$\phi_5 = \rho_1 + \beta\phi_2 > 0.$$

Then, I decompose $ln(A_t)$ in Equation (39) because $ln(A_t) = ln(A_{t-1}) + ln(\mu) + \xi_t$. Since ξ_t and $ln(A_{t-1})$ are independent of other variables, I get the following results:

$$\phi_3 = \rho_1\alpha_3 + \beta\phi_2\alpha_3 + \beta\phi_3, \text{ and } \phi_4 = \phi_3$$
$$\text{which implies } \phi_3 = \phi_4 = \frac{\rho_1\alpha_3 + \beta\phi_2\alpha_3}{1-\beta} > 0.$$

By taking the result that ϕ_2 is constant and strictly positive to the representation of n_t and q_t, I obtain constant solutions for n_t and q_t and use notation n and q for them hereafter. Therefore, all other terms on right hand side are constants or ϕ_1-related, and the value ϕ_1 is solved as a constant. It is intuitive that all coefficients except the intercept are positive. It is also found that n and q lie in meaningful ranges: $\bar{n} > n > 0$ and $1 > q > 0$. Moreover, since all coefficients $\{\phi_j\}_{j=1,\ldots,5}$ are unique solutions, the $\{n, q\}$ are unique.

Therefore, I have demonstrated that the proposed value function $V(k_t, A_{t-1}, \xi_t, \varepsilon_t)$ is valid and provides a unique solution that satisfies general economic intuitions. Last, but not least, I derive two main results: First, $c_t = qF_t(\cdot)$ or equivalently, $k_{t+1} = (1-q)F_t(\cdot)$. This can be used directly in the decentralized economy in the context. Second, the labor input is constant ($n_t = \frac{\alpha_1(\rho_1+\beta\phi_2)\bar{n}}{\rho_2+\alpha_1(\rho_1+\beta\phi_2)}$), which will be verified in the decentralized economy.

B. U.S. data in details

1. Gross domestic product (GDP) per capita: the real, seasonally adjusted GDP (ID: GDPC96) divided by population. Data is obtained from Federal Reserve Economic Data (FRED).[32] The unit is in billions of chained U.S. dollars in 2000.

2. Population: the total population including all ages and armed forces overseas (ID: POP) from FRED. Since the data is in monthly frequency, I use the three-month average as the quarterly population. The unit is in thousands.

3. Labor input: the average weekly work hours of production workers (ID: CES0500000005) divided by the hours of five days. Data is obtained from the Department of Labor, Bureau of Labor Statistics.[33] The unit is hours, and the series is seasonally adjusted. The data is in monthly frequency, and I use the three-month average number as the quarterly data.

4. Investment and capital per capita: the total investment per capita is the sum of real gross private domestic investment (ID: GPDIC96), real federal nondefense gross investment (ID: NDGIC96), and real state and local government gross investment (ID: SLINVC96) divided by the population. All data are from FRED. All data are seasonally adjusted. The unit is in billions of chained U.S. dollars in 2000. To compute the capital, I accumulate the total investment of each quarter since 1947Q1 with depreciation rate 2.5% per quarter.

5. Price and inflation: The price level used here is the consumer price index for all urban consumers including all items (ID: CPIAUCSL). It is seasonal adjusted (monthly) and its base period is 1982-84 (= 100). I use the three-month average of the price index as the price level of that quarter. The data is obtained from FRED, and the original source is the Department of Labor, Bureau of Labor Statistics.

6. Market returns: I consider the CRSP (Center for Research in Security Prices) value-weighted index returns and Standard & Poor's 500 (S&P500) index returns as two proxies for market

[32] FRED: http://research.stlouisfed.org/fred2/

[33] Website of U.S. Department of Labor, Bureau of Labor Statistics: http://www.bls.gov/

portfolio returns. I also consider inflation-adjusted returns, for which I adjust market returns with inflation measured by the growth rate of the price level. The CRSP (Center for Research in Security Prices) value weighted returns: from Kenneth French's website.[34] S&P500 index returns series: from CRSP Monthly Stock dataset, which does not include the dividends.

7. Risk-free asset returns: One month treasury-bill returns from Ibbotson Associates is also available from Kenneth French's website.

8. U.S. patent applications: Because there exists a lag between the application date and granted date of each patent, the patent application number in the period 2002-2004 requires estimation: I multiply the number of filed applications reported by USPTO with an estimated granted ratio. Moreover, I find some inappropriate data points (1982Q2-Q3 and 1995Q1-Q2) that appear unreasonable jump up-and-downs, so I substitute them using an interpolation method.

9. U.S. R&D expenses: For some firms that report only annual R&D expenses, I divide their annual expenses by four as their quarterly expenses. Because the total R&D expenses in 2004Q4 are so low that I need to treat that as an outlier, I have the sample period in empirical study ends at 2004Q3. Nevertheless, I get identical results with sample period 1991Q2–2003Q4.

10. *cay*: from Lettau and Ludvigson (2001).[35] I prolong the original *cay* data series to 2004Q3 based on the same formula ($cay = c - 0.3054a - 0.5891y$) with updated c, a, y available from the same source.

11. Labor income to consumption ratio (SW): the predictor SW is constructed following the calculation described in Santos and Veronesi (2006). They define the (aggregate) labor income 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).[36] All items are in National Income and Product Accounts (NIPA) Table 2.1: Personal Income and Its Disposition. Data are from FRED database.

12. Relative riskfree rate (RRel): current one-month Treasury bill rate minus the previous 4-quarter average of that rate.

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[34] I thank Kenneth French for sharing the data. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

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

[36] The consumption defined here is the personal consumption expenditures on nondurable goods and services (line 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 my study.

13. Dividend-price ratio: the dividend-price ratio series is obtained from Robert Shiller's website.[37] The ratio is based on S&P500 composite index. Since the dividend data is not available after June 2004, I assume that the dividends in September and December 2004 are at the same level as June 2004.

14. Dividend-earnings ratio: the dividend-earnings ratio is also obtained from Robert Shiller's website.

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

16. Default premium (Default): Moody's BAA corporate bond rate minus AAA corporate bond rate, both from FRED.

C. U.K. data in details

Except patent data, all data are taken from the Office for National Statistics, U.K.[38]

1. British patent: I manually collect the quarterly number of all British patent applications reported in the *Patents and Designs Journal* published weekly by the Patent Office of the United Kingdom. In each issue, I record the page numbers and estimate the number of applications on each page to estimate the patent applications. The *Patents and Designs Journal* has not changed its version since Issue 5212 that is published in January 1989.

2. Gross domestic product (GDP) per capita: the real, seasonally adjusted GDP (ID: IHXW) divided by U.K. population. The unit is in millions of 2003 £.

3. Population: I use the people in employment of UK: aged 16 and older (ID: MGRN LFS) instead of the total population because the latter is available in yearly frequency only in my search. The series is seasonally adjusted, and the unit is in thousands.

4. Labor input: the average weekly work hours. I compute that number by dividing the total actual weekly hours worked (ID: YBUS LFS) (in millions) by population and hours of five days. Both series are seasonally adjusted.

5. Investment input per capita: I divide the real total gross fixed capital formation (ID: NPQT) by population. Both series are seasonally adjusted. The unit is in millions of 2002 £.

6. U.K. stock returns: the FTSE 100 index returns obtained from Yahoo!Finance.[39]

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

[38] http://www.statistics.gov.uk

[39] http://finance.yahoo.com

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Table 1: GMM test for the model

In this table, I report the results of GMM test for the null hypothesis composed of three moment conditions. I use the standard two-step procedure to estimate the mean and standard deviations of the parameters in my model, and calculate Hansen's J-test statistic (1982). The moment conditions derived from the Model 1 are:

$0 = E_t[\Delta F_{t+1} - (\Delta n_{t+1})^{\alpha_1}(\Delta k_{t+1})^{\alpha_2}\gamma_{t+1}^{\alpha_3}]$

$0 = E_t[R^s_{t+1} - \beta^{-1}\Delta F_{t+1}]$

$0 = E_t[m_{t+1}R^s_{t+1} - 1]$

$0 = E_t[r^s_{t+1} - const - \alpha_2\alpha_3\xi_t]$,

The pricing kernel $m_{t+1} = \beta(\Delta n_{t+1})^{-\alpha_1}(\Delta k_{t+1})^{-\alpha_2}(\gamma^{pat}_{t+1})^{-\alpha_3}(\Delta\varepsilon_{t+1})^{-1}$, where Δn denotes labor growth, Δk denotes capital growth, γ^{pat} denotes the patent growth, ξ^{pat} denotes the patent shocks, and $\Delta\varepsilon$ denotes the non-technology shock growth. The alternative hypotheses for free parameters are: $\beta < 1$, and $\alpha_1,\ \alpha_2,\ \alpha_3 > 0$. I use the Newey-West's (1987) covariance matrix estimate with lag number 4 and 8, while the lag 4 is commonly used in the literature according the rule $floor(T^{1/3}) = 4$. The sample period is 1977Q1–2004Q3.

Panel A: Newey-West (lag 4)

Parameters	Coeff.	Std. Err.	Null	t-stat.	p-value
β	0.971	0.001	1.00	-31.75	0.000
α_1	0.640	0.316	0.00	2.03	0.021
α_2	0.291	0.153	0.00	1.91	0.028
α_3	0.622	0.243	0.00	2.55	0.011
$const$	0.031	0.001	0.00	42.51	0.000
J-statistic:	7.84				
Prob($\mathcal{X}^2(12-5) > J$-statistic):			0.347		

Panel B: Newey-West (lag 8)

Parameters	Coeff.	Std. Err.	Null	t-stat.	p-value
β	0.971	0.001	1.00	-37.79	0.000
α_1	0.590	0.228	0.00	2.59	0.005
α_2	0.335	0.117	0.00	2.86	0.002
α_3	0.536	0.171	0.00	3.14	0.001
$const$	0.031	0.001	0.00	47.96	0.000
J-statistic:	6.60				
Prob($\mathcal{X}^2(12-5) > J$-statistic):			0.472		

Table 2: Summary statistics

Panel A reports the descriptive statistics of all variables, and Panel B reports the contemporaneous correlation between technology shocks and stock returns and other predictors. The sample period for most variables is 1976Q1–2004Q3, except for patent shocks (1977Q1–2004Q3), R&D growth (1991Q1–2004Q3), R&D shocks (1991Q2–2004Q3), and British data (1991Q1–2004Q4). The t statistics reported are the results of testing whether the means of variables are different from zero. Selected Augmented Dickey-Fuller (ADF) statistics of some highly autocorrelated variables are reported in the last column, and the following $*$ denotes that ADF test (with intercept) rejects the existence of a unit root with 10% significance level. The lag number of models in computing ADF statistics are decided according to the model's Durbin-Watson statistic and the t-statistic of coefficients of lagged variable as regressor.

Panel A: Descriptive statistics									
Variables	Mean (%)	Median (%)	Max. (%)	Min. (%)	Std. dev. (%)	t-stat. (zero)	1st order autocor.	ADF stat.	
Asset returns									
CRSPvw	3.064	3.831	19.202	-25.998	8.183	4.033	-0.043		
S&P500	2.240	2.437	18.952	-26.432	7.794	3.095	-0.001		
r^f	1.494	1.342	3.737	0.220	0.746	21.575	0.949	-1.44	
Inflation	0.895	0.694	2.770	0.195	0.576	16.723	0.905	-2.37	$*$
FTSE 100	1.465	1.393	16.156	-20.071	7.932	1.431	-0.003		
Technology-related variables									
r_t^{pat}	0.543	0.516	0.779	0.341	0.136	42.965	0.989	-0.47	
r_t^{rd}	1.175	1.189	1.383	0.799	0.127	69.490	0.965	2.17	
r_t^{UKpat}	0.459	0.362	0.951	0.309	0.163	162.599	0.997	-6.79	$*$
ξ_t^{pat}	0.006	0.005	0.085	-0.095	0.028	2.481	0.633		
ξ_t^{rd}	-0.011	0.000	0.089	-0.207	0.062	-1.269	0.820		
ξ_t^{UKpat}	-0.001	-0.002	0.046	-0.062	0.021	-0.445	0.463		
Other predictors									
cay	60.581	60.899	63.710	56.477	1.307		0.863	-2.86	$*$
SW	89.462	88.207	98.178	82.670	4.238		0.982	-1.96	
RRel	-0.024	-0.021	0.811	-0.955	0.326		0.668		
$d-p$	-355.492	-345.123	-277.936	-449.807	48.153		0.989	-0.37	
$d-e$	-77.683	-84.122	-26.928	-118.980	20.362		0.951	-1.20	
Term	1.793	1.852	3.800	-1.430	1.267		0.861	-2.95	$*$
Default	1.084	0.983	2.513	0.560	0.432		0.912	-2.42	

Panel B: Correlation between technology shocks and other variables									
	CRSPvw	S&P500	cay	SW	RRel	$d-p$	$d-e$	Term	Default
ξ_t^{pat}	0.067	0.094	0.155	-0.161	0.179	-0.023	-0.114	0.145	-0.173
ξ_t^{rd}	0.134	0.191	-0.152	-0.107	0.263	0.215	0.048	-0.384	-0.388
	FTSE100								
ξ_t^{UKpat}	-0.198								

Table 3: Short-term forecasting for CRSP index returns: Patent shocks and others

I regress the log CRSP inflation-adjusted returns of time $t+1$ on patent shocks and other predictors in time t (1-step ahead forecasting): $r^s_{t+1} = X_t\beta + e_{t+1}$, where X_t denotes a vector of predictors, β denotes a vector of coefficients, and e_{t+1} denotes the residual. "Lag Ret" denotes the lagged CRSP inflation-adjusted returns, i.e., r^s_t. The descriptions of all other predictive variables can be found in the context or Appendix B. Numbers in parentheses are the t-statistics of Newey-West's estimator (1987), adjusted for serial correlation and heteroskedasticity up to four lags. The sample period is 1977Q1–2004Q3. I use the standardized patent shocks as predictor in Panel A, and the original patent shocks as predictor in Panel B. Numbers in bold indicate p-values of t-statistics (one-sided) that are smaller than 5%.

Panel A: Standardized patent shocks and other predictors

♯	Const.	Lag Ret	Stand. ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
1	**0.02**		**0.02**						0.05
	(3.07)		(3.37)						
2	**0.02**	-0.05	**0.02**						0.04
	(3.03)	(-0.70)	(3.44)						
3	-0.40		**0.02**	0.69					0.05
	(-1.07)		(3.09)	(1.14)					
4	-0.08		**0.02**		0.12				0.04
	(-0.51)		(3.21)		(0.64)				
5	**0.02**		**0.02**			**-3.49**			0.06
	(3.05)		(3.55)			(-1.77)			
6	**0.10**		**0.02**				0.02		0.06
	(1.70)		(3.38)				(1.29)		
7	0.03		**0.02**					0.01	0.04
	(1.05)		(3.27)					(0.35)	

Panel B: Patent shocks and other predictors

♯	Const.	Lag Ret	ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
8	**0.02**		**72.83**						0.05
	(2.17)		(3.38)						
9	**0.02**	-0.05	**74.24**						0.04
	(2.16)	(-0.70)	(3.43)						
10	-0.40		**67.83**	0.69					0.05
	(-1.09)		(3.09)	(1.14)					
11	-0.09		**75.61**		0.12				0.04
	(-0.54)		(3.21)		(0.65)				
12	**0.02**		**80.42**			**-3.49**			0.06
	(2.03)		(3.55)			(-1.77)			
13	0.09		**73.76**				0.22		0.06
	(1.63)		(3.38)				(1.30)		
14	0.03		**73.96**					0.01	0.04
	(0.90)		(3.27)					(0.35)	

Table 4: Short-term forecasting for CRSP index returns: R&D shocks and others

I regress the log CRSP inflation-adjusted returns of time $t+1$ on R&D shocks and other predictors in time t (1-step ahead forecasting): $r^s_{t+1} = X_t\beta + e_{t+1}$, where X_t denotes a vector of predictors, β denotes a vector of coefficients, and e_{t+1} denotes the residual. "Lag Ret" denotes the lagged CRSP inflation-adjusted returns, i.e., r^s_t. The descriptions of all other predictive variables can be found in the context or Appendix B. Numbers in parentheses are the t-statistics of Newey-West's estimator (1987), adjusted for serial correlation and heteroskedasticity up to four lags. The sample period is 1991Q2–2004Q3. I use the standardized R&D shocks as predictor in Panel A, and the original R&D shocks as predictor in Panel B. Numbers in bold indicate p-values of t-statistics (one-sided) that are smaller than 5%.

Panel A: Standardized R&D shocks and other predictors									
♯	Const.	Lag Ret	Stand. ξ^{rd}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
1	0.02		**0.03**						0.04
	(1.25)		(2.02)						
2	0.02	-0.10	**0.03**						0.03
	(1.23)	(-0.87)	(2.08)						
3	-0.57		**0.03**	0.98					0.06
	(-1.52)		(1.97)	(1.58)					
4	-0.60		**0.03**		0.72				0.04
	(-0.88)		(2.03)		(0.91)				
5	0.02		0.02			2.88			0.03
	(1.21)		(1.59)			(0.52)			
6	**0.22**		**0.02**				0.05		0.06
	(1.68)		(1.83)				(1.51)		
7	0.03		**0.02**					0.01	0.04
	(1.05)		(3.27)					(0.18)	
Panel B: R&D shocks and other predictors									
♯	Const.	Lag Ret	ξ^{rd}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
8	**0.02**		**43.88**						0.04
	(1.88)		(2.03)						
9	**0.02**	-0.10	**46.92**						0.03
	(1.80)	(-0.87)	(2.08)						
10	-0.57		**51.80**	0.98					0.06
	(-1.51)		(1.98)	(1.58)					
11	-0.60		**46.37**		0.72				0.05
	(-0.87)		(2.03)		(0.91)				
12	**0.02**		38.47			2.87			0.03
	(1.74)		(1.60)			(0.52)			
13	**0.22**		**38.64**				0.05		0.06
	(1.71)		(1.83)				(1.51)		
14	0.03		**44.92**					0.01	0.02
	(0.86)		(1.95)					(0.18)	

Table 5: Long-term forecasting for CRSP index returns: Patent shocks and R&D shocks

In this table I examine the long-term predictability of two technology shocks (standardized ξ^{pat} and standardized ξ^{rd}). I use CRSP index return as stock market returns. I run the following long-term predictive regression: $r^s_{t+k} + ... + r^s_{t+1} = a_0 + a_1\,\xi_t + u_{t+k,t}$, where k denotes the length of forecasting horizon and $u_{t+k,t}$ denotes the overlapping residual. The sample sizes involving predictors ξ^{pat} and ξ^{rd} are 1977Q1–2004Q3 and 1991Q2–2004Q3, respectively. Numbers in brackets are t-statistics based on Hodrick 1B (1992) standard errors that are designed for cumulative predictive regression. Numbers in boldface indicate significance under 5% level (one-sided) with 1B standard errors. I simply brief the process of computing 1B standard errors here: With the parameter $a = [a_0\; a_1]'$, I know that $\sqrt{T}(\hat{a} - a) \sim N(0, \Sigma)$, where $\Sigma = Z_0^{-1} S_0 Z_0^{-1}$ and $Z_0 = E[xx']$ with $x_t = [1\;\xi_t]$. I first regress future one-period simple logarithmic returns r^s_{t+1} on a constant and get residuals ϵ_{t+1} (because the under the null, the coefficients of predictors zre zero). Estimator of S_0 is

$$\hat{S}_0 = \frac{1}{T}\sum_{t=k}^{T}\left[\epsilon_{t+1}\left(\sum_{i=0}^{k-1} x_{t-i}\right)\right]\left[\epsilon_{t+1}\left(\sum_{i=0}^{k-1} x_{t-i}\right)\right]'.$$

Sample analog of Z_0 is $\hat{Z}_0 = 1/T\,\sum_{t=k}^{T} x_t\, x_t'$.

♯	const.	stand ξ^{pat}	stand ξ^{rd}	$adj - R^2$
Panel A: Future 4-Quarter Returns				
♯	const.	stand ξ^{pat}	stand ξ^{rd}	$adj - R^2$
1	**0.09**	**0.07**		0.18
	[2.73]	[2.66]		
2	**0.07**		**0.07**	0.07
	[2.06]		[2.51]	
Panel B: Future 8-Quarter Returns				
♯	const.	stand ξ^{pat}	stand ξ^{rd}	$adj - R^2$
3	**0.18**	**0.06**		0.08
	[2.71]	[1.74]		
4	**0.13**		**0.10**	0.04
	[1.97]		[2.51]	
Panel C: Future 12-Quarter Returns				
♯	const.	ξ^{pat}	ξ^{rd}	$adj - R^2$
5	**0.26**	**0.10**		0.10
	[2.66]	[2.40]		
6	**0.17**		**0.16**	0.05
	[1.69]		[3.24]	

Table 6: Short-term forecasting for CRSP excess returns: Patent shocks, R&D shocks, and others

I regress the logarithmic CRSP inflation-adjusted excess returns of time $t+1$ on standardized patent shocks (Panel A), standardized R&D shocks (Panel B), and other predictors in time t (1-step ahead forecasting): $r^s_{t+1} - r^f_{t+1} = X_t\beta + e_{t+1}$, where X_t denotes a vector of predictors, β denotes a vector of coefficients, and e_{t+1} denotes the residual. "Lag Ret" denotes the lagged CRSP excess returns, i.e., $r^s_t - r^f_t$. The descriptions of all other predictive variables can be found in the context or Appendix B. The sample sizes involving predictors stand ξ^{pat} and stand ξ^{rd} are 1977Q1–2004Q3 and 1991Q2–2004Q3, respectively. Numbers in parentheses are the t-statistics of Newey-West's estimator (1987), adjusted for serial correlation and heteroskedasticity up to four lags. Numbers in bold indicate p-values of t-statistics (one-sided) that are smaller than 5%.

Panel A: Standardized patent shocks and other predictors									
♯	Const.	Lag Ret	Stand. ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
1	0.01		**0.02**						0.05
	(0.85)		(3.53)						
2	0.01	-0.05	**0.02**						0.05
	(0.85)	(-0.62)	(3.61)						
3	-0.40		**0.02**	0.68					0.06
	(-1.05)		(3.29)	(1.07)					
4	0.01		**0.02**		0.00				0.04
	(0.03)		(3.23)		(0.00)				
5	0.00		**0.02**			**-4.51**			0.08
	(0.74)		(3.78)			(-2.49)			
6	0.04		**0.02**				0.01		0.05
	(0.72)		(3.47)				(0.61)		
7	0.02		**0.02**					0.02	0.05
	(0.86)		(3.40)					(0.64)	

Panel B: Standardized R&D shocks and other predictors									
♯	Const.	Lag Ret	ξ^{rd}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
8	0.01		**0.03**						0.03
	(0.51)		(1.86)						
9	0.01	-0.10	**0.03**						0.02
	(0.53)	(-0.81)	(1.90)						
10	-0.65		**0.03**	**1.10**					0.06
	(-1.68)		(1.85)	(1.72)					
11	-0.70		**0.03**		0.83				0.04
	(-1.02)		(1.88)		(1.03)				
12	0.01		0.02			2.16			0.02
	(0.55)		(1.47)			(0.38)			
13	0.21		**0.02**				0.05		0.05
	(1.65)		(1.66)				(1.54)		
14	0.02		**0.03**					0.01	0.02
	(0.54)		(1.79)					(0.30)	

Table 7: Long-term forecasting for CRSP excess returns: Patent shocks and R&D shocks

In this table I examine the long-term predictability of two technology shocks (standardized ξ^{pat} and standardized ξ^{rd}). I use CRSP excess return as stock market returns. I run the following long-term predictive regression: $r^s_{t+k} + ... + r^s_{t+1} = a_0 + a_1\,\xi_t + u_{t+k,t}$, where k denotes the length of forecasting horizon and $u_{t+k,t}$ denotes the overlapping residual. The sample sizes involving predictors ξ^{pat} and ξ^{rd} are 1977Q1–2004Q3 and 1991Q2–2004Q3, respectively. Numbers in brackets are t-statistics based on Hodrick 1B (1992) standard errors that are designed for cumulative predictive regression. Numbers in boldface indicate significance under 5% level (one-sided) with 1B standard errors.

Panel A: Future 4-Quarter Returns				
♯	const.	stand ξ^{pat}	stand ξ^{rd}	$adj-R^2$
1	0.03	**0.07**		0.18
	[0.81]	[2.42]		
2	0.03		**0.06**	0.05
	[0.99]		[2.43]	
Panel B: Future 8-Quarter Returns				
♯	const.	stand ξ^{pat}	stand ξ^{rd}	$adj-R^2$
3	0.05	**0.07**		0.08
	[0.75]	[1.67]		
4	0.06		**0.07**	0.02
	[0.93]		[2.03]	
Panel C: Future 12-Quarter Returns				
♯	const.	ξ^{pat}	ξ^{rd}	$adj-R^2$
5	0.07	**0.11**		0.12
	[0.72]	[2.14]		
6	0.06		**0.13**	0.03
	[0.61]		[3.26]	

Table 8: Short-term forecasting for CRSP index returns: 1977Q1–1995Q4

For the sample period 1977Q1–1995Q4, I regress the log CRSP inflation-adjusted returns of time $t+1$ on patent shocks and other predictors in time t (1-step ahead forecasting): $r^s_{t+1} = X_t\beta + e_{t+1}$, where X_t denotes a vector of predictors, β denotes a vector of coefficients, and e_{t+1} denotes the residual. "Lag Ret" denotes the lagged CRSP inflation-adjusted returns, i.e., r^s_t. The descriptions of all other predictive variables can be found in the context or Appendix B. Numbers in parentheses are the t-statistics of Newey-West's estimator (1987), adjusted for serial correlation and heteroskedasticity up to four lags. I use the standardized patent shocks as predictor in Panel A, and the original patent shocks as predictor in Panel B. Numbers in bold indicate p-values of t-statistics (one-sided) that are smaller than 5%.

Panel A: Standardized patent shocks and other predictors									
♯	Const.	Lag Ret	Stand. ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
1	**0.02**		**0.02**						0.02
	(2.95)		(2.58)						
2	**0.02**	0.00	**0.02**						0.00
	(3.25)	(0.03)	(2.57)						
3	**-1.28**		**0.02**	**2.14**					0.05
	(-2.08)		(2.35)	(2.12)					
4	-0.03		**0.02**		0.06				0.01
	(-0.15)		(2.48)		(0.27)				
5	**0.02**		**0.02**			**-4.07**			0.05
	(3.25)		(3.19)			(-2.04)			
6	**0.21**		**0.03**				0.06		0.04
	(1.79)		(3.33)				(1.60)		
7	0.03		**0.02**					0.00	0.00
	(1.00)		(2.50)					(0.11)	
Panel B: Patent shocks and other predictors									
♯	Const.	Lag Ret	ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
8	**0.02**		**67.67**						0.02
	(2.31)		(2.58)						
9	**0.02**	0.00	**67.66**						0.00
	(2.53)	(0.03)	(2.57)						
10	**-1.29**		**56.29**	**2.14**					0.04
	(-2.09)		(2.35)	(2.12)					
11	-0.03		**71.87**		0.06				0.01
	(-0.18)		(2.48)		(0.27)				
12	**0.02**		**76.70**			**-4.07**			0.05
	(2.58)		(3.19)			(-2.04)			
13	**0.20**		**98.82**				0.06		0.04
	(1.74)		(3.33)				(1.60)		
14	0.02		**67.94**					0.00	0.00
	(0.85)		(2.50)					(0.11)	

Table 9: Two-step-ahead forecasting for CRSP index returns: patent shocks and others

To accommodate the reporting lag, I examine the predictability of patent shocks and other predictors for 2-step ahead stock returns in sample period 1977Q3–2004Q3. Here I regress the logarithmic CRSP inflation-adjusted index returns of time $t+2$ on patent shocks and other predictors in time t: $r^s_{t+2} = X_t\beta + e_{t+2}$. "Lag Ret" denotes the r^s_t. I use the standardized patent shocks as predictor in Panel A, and the original patent shocks as predictor in Panel B. Numbers in parentheses are the t-statistics of Newey-West's estimator (1987), adjusted for serial correlation and heteroskedasticity up to four lags. Numbers in bold indicate p-values of t-statistics (one-sided) that are smaller than 5%.

Panel A: Standardized patent shocks and other predictors									
♯	Const.	Lag Ret	Stand. ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
1	**0.02**		**0.02**						0.08
	(3.16)		(3.47)						
2	**0.02**	-0.00	**0.02**						0.07
	(2.91)	(-0.06)	(3.48)						
3	-0.25		**0.02**	0.46					0.07
	(-0.59)		(3.31)	(0.65)					
4	-0.13		**0.03**		0.18				0.08
	(-0.80)		(3.45)		(0.93)				
5	**0.02**		**0.03**			**-2.51**			0.08
	(3.16)		(3.53)			(-1.19)			
6	**0.10**		**0.02**				0.02		0.09
	(1.67)		(3.60)				(1.28)		
7	0.03		**0.02**					0.01	0.07
	(0.99)		(3.40)					(0.28)	
Panel B: Patent shocks and other predictors									
♯	Const.	Lag Ret	ξ^{pat}	cay	SW	RRel	$d-p$	$d-e$	$adjR^2$
8	**0.02**		**88.00**						0.08
	(2.08)		(3.47)						
9	**0.02**	-0.00	**88.13**						0.07
	(1.95)	(-0.06)	(3.48)						
10	-0.26		**84.65**	0.46					0.07
	(-0.60)		(3.31)	(0.64)					
11	-0.14		**92.03**		0.18				0.08
	(-0.83)		(3.45)		(0.93)				
12	**0.01**		**93.48**			**-2.51**			0.08
	(1.99)		(3.53)			(-1.19)			
13	0.09		**88.70**				0.22		0.09
	(1.58)		(3.60)				(1.28)		
14	0.02		**88.91**					0.01	0.07
	(0.81)		(3.40)					(0.28)	

Table 10: Check for possible small sample biases

Here I check the correlation between predictive regression residuals and predictor's innovations because Stambaugh (1986, 1999) show that the predictive regressor's coefficient is upward biased and may deviate substantially from the standard regression setting. In this table, I report possible small sample biases of the predictability of the patent shocks (ξ^{pat}) and R&D shocks (ξ^{rd}). In Panel A, I estimate an AR(1) model for ξ: $\xi_{t+1} = a_0 + a_1 \xi_t + \epsilon^{\xi}_{t+1}$. In Panel B, I use OLS regression to estimate the predictability of CRSP index returns, $r^s_{t+1} = b_0 + b_1 \xi_t + \epsilon^r_{t+1}$. In Panel C, I regress the residuals obtained in Panel B on AR(1) residuals obtained in Panel A, $\epsilon^r_{t+1} = c_0 + c_1 \epsilon^{\xi}_{t+1} + e_{t+1}$. Finally, I assume that the downward bias of a_1 is $-(1+3a_1)/T$, and the biases in b_1 can be estimated as $Bias = -c_1(1+3a_1)/T$ and are reported in Panel B for comparison. The corrected b^0_1 is therefore $b_1 - Bias$. All t-statistics are based on Newey-West's (1987) standard errors. Sample periods: 1977Q1–2004Q3 for patent shock, and 1991Q2–2004Q3 for R&D shock.

Panel A	**AR(1) structure of ξ:** $\xi_{t+1} = a_0 + a_1 \xi_t + \epsilon^{\xi}_{t+1}$				
	a_0	a_1	$t(a_1)$	$adjR^2$	
ξ^{pat}	0.012	0.640	8.37	0.41	
ξ^{rd}	-0.023	0.864	8.65	0.59	
Panel B	**Predictive regression for CRSP:** $r^s_{t+1} = b_0 + b_1 \xi_t + \epsilon^r_{t+1}$				
	b_0	b_1	$t(b_1)$	$adjR^2$	$Bias$
ξ^{pat}	0.021	0.020	3.38	0.05	0.00029
ξ^{rd}	0.015	0.028	2.02	0.04	0.00047
Panel C	$\epsilon^r_{t+1} = c_0 + c_1 \epsilon^{\xi}_{t+1} + e_{t+1}$				
	c_0	c_1	$t(c_1)$	$adjR^2$	
ξ^{pat}	0.000	-0.011	-1.03	0.00	
ξ^{rd}	0.000	-0.006	-0.30	-0.02	

Table 11: Production function specification of U.K.

I run the ordinary least squares regression with and without technology:

Panel A: $ln(\triangle F(n_t, k_t, A_t, \varepsilon_t)) = \alpha_1 ln(\triangle n_t) + \alpha_2 ln(\triangle k_t) + \alpha_3 ln(\gamma_t) + \epsilon_t$,

Panel B: $ln(\triangle F(n_t, k_t, A_t, \varepsilon_t)) = \alpha_1 ln(\triangle n_t) + \alpha_2 ln(\triangle k_t) + \epsilon_t$,

where $\triangle$ denotes gross growth rate (e.g., $\triangle F(n_t, k_t, A_t, \varepsilon_t) = F(n_t, k_t, A_t, \varepsilon_t)/F(n_{t-1}, k_{t-1}, A_{t-1}, \varepsilon_{t-1})$). The production output $F(n_t, k_t, A_t, \varepsilon_t)$ is real GDP per worker, labor is the average weekly work hours divided by hours of five days, and the investment is the real gross fixed capital formation per worker. The proxy for technological growth is British patent growth. Details of data are provided in Appendix C, and the sample period is 1991Q1–2004Q4. The standard errors are adjusted for serial correlation and heteroskedasticity up to three lags by Newey-West's (1987) estimator.

Panel A:	**With technological growth**			
	Coef	Std. error	t-stat.	adj-R^2
Labor (α_1)	1.110	0.160	6.91	0.189
Investment (α_2)	0.031	0.033	0.93	
Technology (α_3)	1.571	0.323	4.86	
Panel B:	**Without technological growth**			
	Coef	Std. error	p-value	adj-R^2
Labor (α_1)	1.288	0.184	7.00	0.081
Investment (α_2)	0.134	0.052	2.57	

Table 12: Forecasting FTSE index returns with British patent shocks

In Panel A, I run the short-term predictive regression by regressing the FTSE100 index returns in logs of time t, r_t^{UK}, on the lagged index returns in logs r_{t-1}^{UK} and lagged standardized British patent shocks ξ_{t-1}^{UKpat}: $r_t^{UK} = a_0 + a_1 r_{t-1}^{UK} + a_2 \xi_{t-1}^{UKpat}$. In Panel B, I run the long-term predictive regression by regressing the cumulative h-period future logarithmic FTSE100 index returns since time t, $r_t^{UK} + r_{t+1}^{UK} + ... + r_{t+h-1}^{UK}$, on lagged British patent shock ξ_{t-1}^{UKpat}: $r_t^{UK} + r_{t+1}^{UK} + ... + r_{t+h-1}^{UK} = a_0 + a_2 \xi_{t-1}^{UKpat}$. The sample period is 1991Q1–2004Q4. Numbers in brackets are the t-statistics based on Hodrick 1b (1992) estimation. Numbers in bold indicate p-values of t-statistics (one-sided) that are smaller than 5%.

Panel A: Short-term forecasting				
♯	a_0	a_1	a_2	adj-R^2
1	0.015		**0.021**	0.07
	(1.56)		(2.35)	
2	0.013	-0.122		0.00
	(1.14)	(-1.20)		
3	0.017	-0.167	**0.023**	0.08
	(1.50)	(-1.67)	(2.38)	
Panel B: Long-term forecasting				
♯	a_0	a_1	a_2	adj-R^2
h=4	0.051		0.012	-0.01
	[1.29]		[0.39]	
h=8	0.090		-0.009	-0.01
	[1.13]		[-0.23]	
h=12	0.140		-0.037	0.00
	[1.15]		[-0.74]	

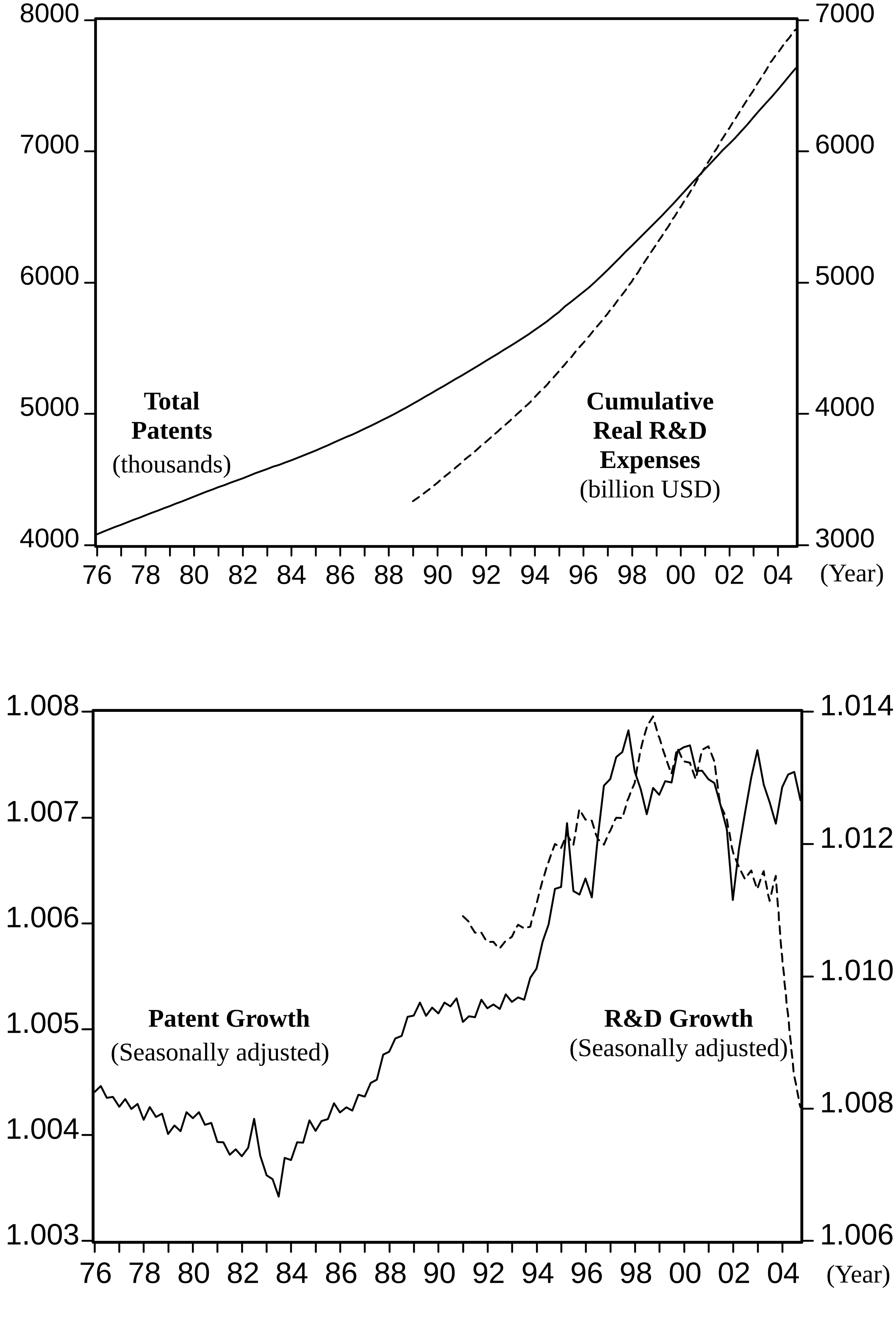


Figure 1. Accumulation and growth of U.S. patents and R&D expenses

Upper Panel: The solid line denotes the total successful patent applications (in thousands), and the dashed line denotes cumulative real R&D expenses (in billions of USD). Lower Panel: The solid line denotes the growth rate of total successful patent applications, and the dotted line denotes the growth rate of cumulative real industrial R&D expenses.

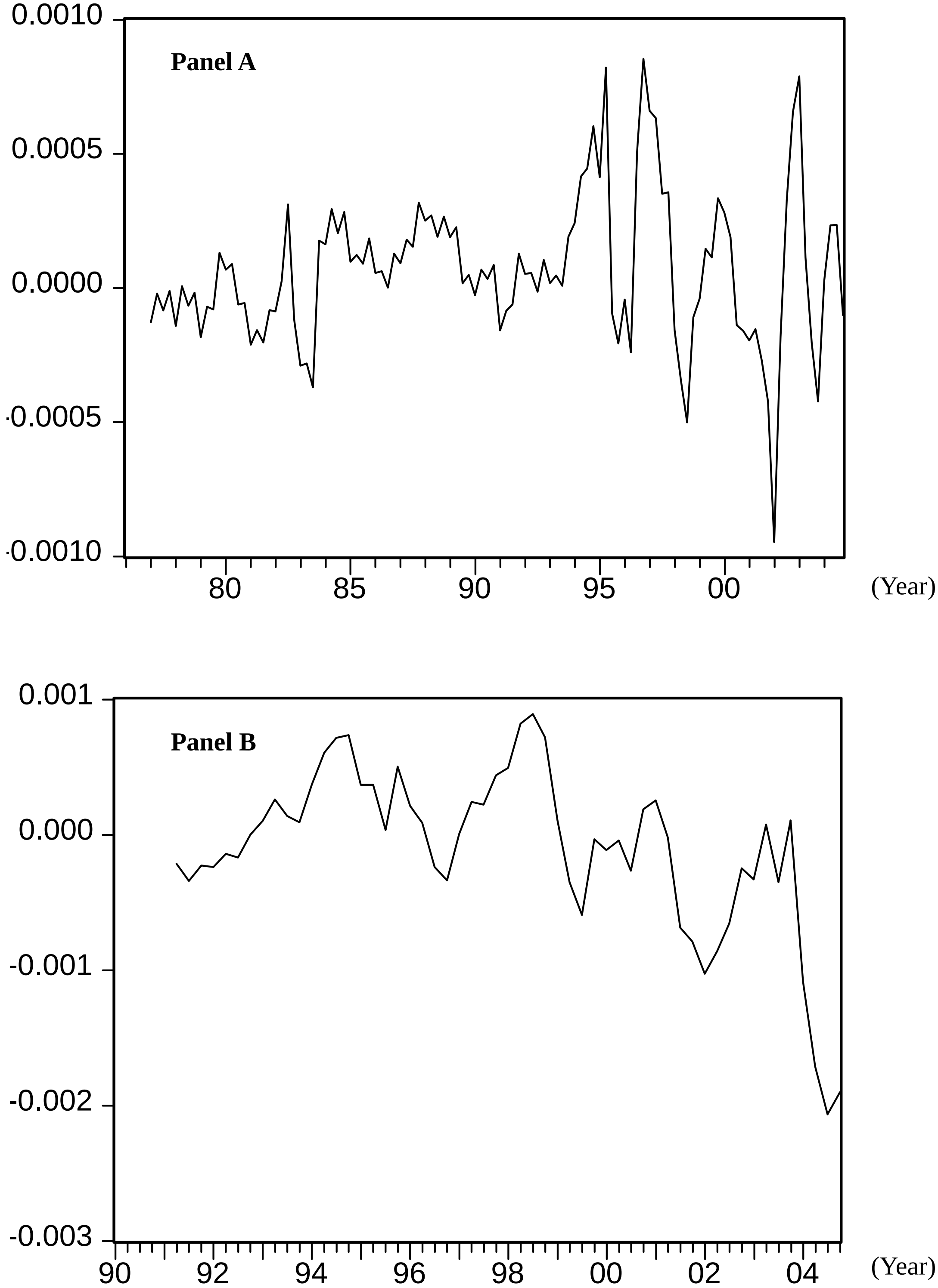


Figure 2. Time series of U.S. patent shocks and R&D shocks

Panel A: U.S. patent shocks; Panel B: U.S. R&D shocks. The details are provided in the context.

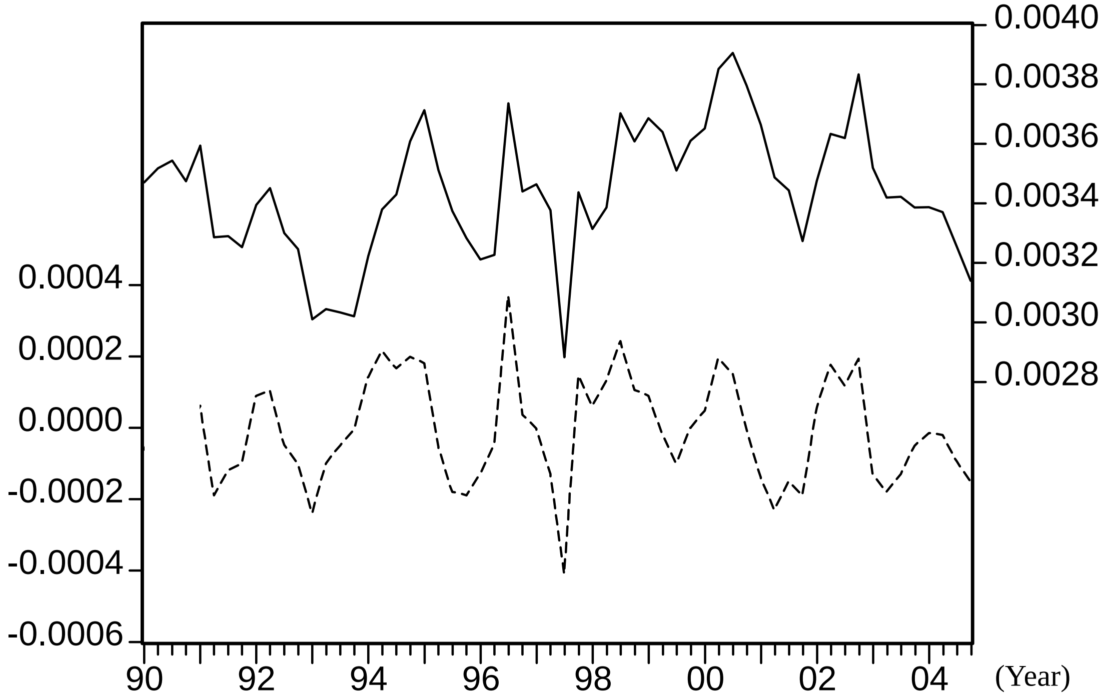
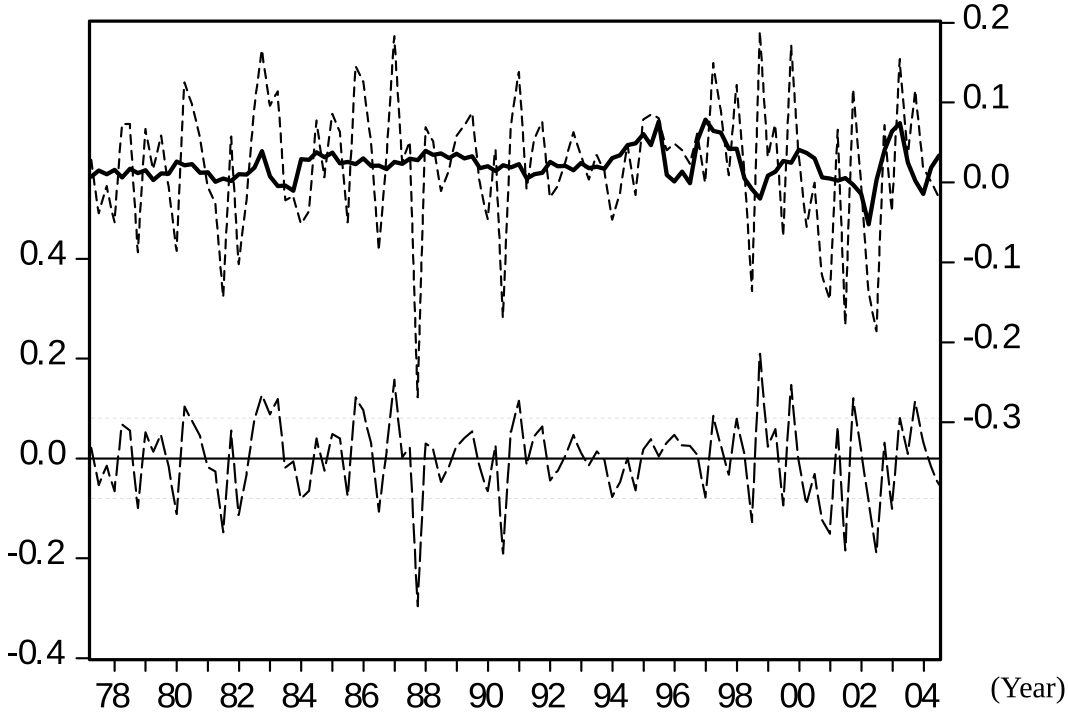


Figure 3. Time series of U.K. patent growth and shocks

The solid line denotes the time series of seasonally adjusted growth of total British patent applications, and the dashed line denotes the times series of British patent shocks.



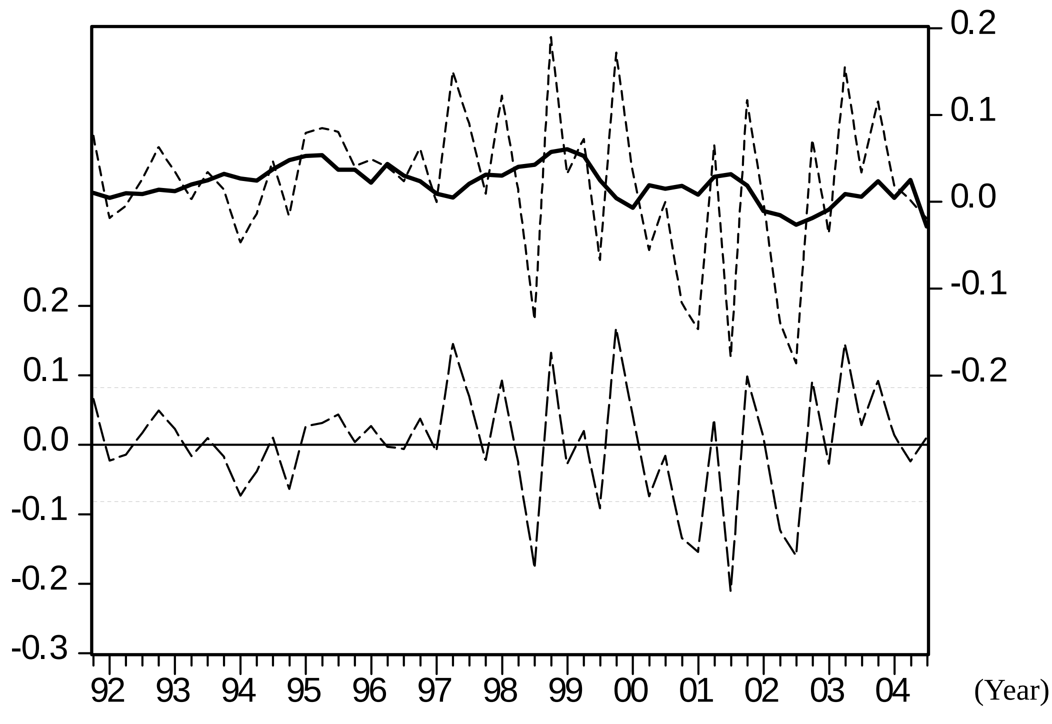


Figure 4. CRSP index returns and forecasts based on technology shocks

Two proxies for technology shocks: standardized patent shocks in the upper figure, and standardized R&D shocks in the lower figure. The bold solid line and dotted line on the top of each figure denote the forecasted and realized CRSP index returns, respectively. The forecasts are obtained from 1-step ahead predictive regression with the technology shocks and an intercept as regressors (#1 in Tables 4 and 5). The dashed line on the bottom of each figure denotes the series of forecasting residuals. Left vertical axis is for predictive residuals, and right vertical axis is for returns and forecasts.

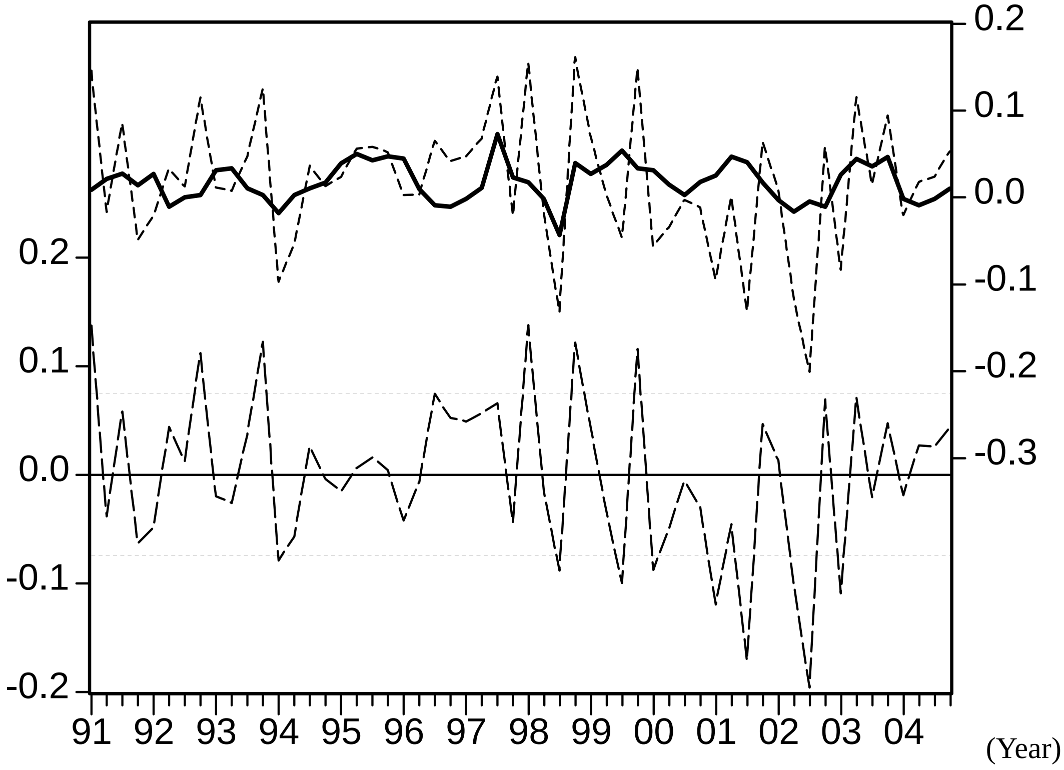


Figure 5. FTSE100 index returns and forecasts based on U.K. technology shocks

The bold solid line and dotted line on the top of each figure denote the forecasted and realized FTSE100 index returns in logs, respectively. The forecasts are obtained from 1-step ahead predictive regression using U.K. technology shocks and a constant as regressors (Table 12, #1). The dashed line on the bottom of figure denotes the series of predictive residuals. Left vertical axis is for predictive residuals, and right vertical axis is for returns and forecasts.