ISSN 0956-8549-645

# Technology Adoption, Vintage Capital and Asset Prices

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**DISCUSSION PAPER NO 645**

**DISCUSSION PAPER SERIES**

**January 2010**

**Xiaoji Lin is an Assistant Professor of Finance at LSE. He received his PhD in Finance from the University of Minnesota. His current research focuses on theoretical and empirical asset pricing in connection with corporate finance, macroeconomics and international finance. His research applies new classical macroeconomics to understand the driving forces behind the cross section of stock returns. One of his articles was awarded the Trefftzs Award by the Western Finance Association in 2008.** 

# Technology Adoption, Vintage Capital and Asset Prices

Xiaoji Lin*

January 12, 2010

**Abstract**

We study technology adoption, risk and expected returns using a dynamic equilibrium model with production. The central insight is that optimal technology adoption is an important driving force of the cross section of stock returns. The model predicts that technology adopting firms are less risky than non-adopting firms. Intuitively, by preventing firms from freely upgrading existing capital to the technology frontier, costly technology adoption reduces the flexibility of firms in smoothing dividends, and hence generates the risk dispersion between technology adopting firms and non-adopting firms. The model explains qualitatively and in many cases quantitatively empirical regularities: (i) The positive relation between firm age and stock returns; (ii) firms with high investment on average are younger and earn lower returns than firms with low investment; and (iii) growth firms on average are younger than value firms, and the value premium is increasing in firm age.

JEL Classification: E23, E44, G12

Keywords: Technology Adoption, Vintage Capital, Firm Age, Investment, Stock Returns

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# 1 Introduction

We investigate technology adoption and the cross sectional asset returns in a dynamic equilibrium model in which technology adoption occurs at firm level [Greenwood and Yorukoglu 1997; Cooper, Haltiwanger and Power 1999].[1] The central insight is that optimal technology adoption is an important driving force of the cross section of stock returns.

This paper contributes to the literature in two folds. Theoretically, by incorporating endogenous technology adoption and vintage capital to the investment-based asset pricing framework (e.g., Zhang 2005), the model simultaneously explains well-document empirical facts: (i) The positive relation between firm age and stock returns (Zhang 2006); (ii) the negative relation between investment and average returns (Xing 2009); and (iii) growth firms earn lower average returns than value firms (Fama and French 1992, 1993). Empirically, guided by the theoretical predictions, the paper establishes a series of new findings regarding firm age and expected returns: (i) Firms with high investment on average are younger than firms with low investment; (ii) growth firms on average are younger than value firms; and (iii) the value premium is increasing in firm age. These findings seem to suggest that firm age is an important characteristic of the cross sectional returns.

Our theoretical framework relies on a salient feature, costly technology adoption. In the model, technology frontier grows exogenously to which all firms have access. Facing both aggregate and firm-specific productivity shocks, firms choose to adopt the latest technology at a cost or keep operating the existing vintage capital. Costly technology adoption restricts the degree of firms' flexibility in smoothing dividend streams. Through optimal investment, costly adoption gives rise to the risk dispersion between technology-adopting firms and non-adopting firms. The model predicts that firms that adopt the latest technology or operate the new vintage capital are less risky than non-adopting firms.

Intuitively, in good times, both technology-adopting firms and non-adopting firms can take the advantage of favourable economic conditions: Adopting firms take a cost to upgrade the latest technology whereas non-adopting firms still operate the exiting vintage capital

[1] See Parente and Prescott (1994) and Laitner and Stolyarov (2003) for an analysis of aggregate technology adoption.

as their old vintage becomes productive now. As a result, both types of firms covary with aggregate uncertainty and their risk dispersion is low. In bad times, equipped with the latest vintage capital, adopting firms (or firms using new vintage capital) are more productive. In contrast, non-adopting firms cannot upgrade their old vintage capital because it is too costly for them, so their dividend streams covary more with economic downturns than adopting firms. The overall effect is that adopting firms are less risky than non-adopting firms given that the price of risk is particularly high in bad times.[2]

In the model, to advance to the latest vintage capital, firms must make an investment, meaning that technology adoption and capital investment are directly tied together. This relation implies that the more investment firms make, the less risky the firms are. Consistent with the model prediction, firms with higher capital investment on average earn lower expected returns than firms with lower investment in the data.[3] Notably a few papers also predict a negative relation between the expected returns and capital investment (e.g., Cochrane 1991, Liu, Whited and Zhang 2008, Li, Livdan and Zhang 2009, etc), but they rely on a different mechanism of convex capital adjustment costs. Besides, in these models, capital is homogeneous across different vintages. In contrast, in our paper the productivity of vintage capital grows over time following the evolution of exogenous technological frontier. Optimal technology adoption decisions give rise to the inverse relationship between investment and returns.

By linking vintage capital to firm risk, the model sheds light on the relationship between firm age, an important firm characteristic, and expected returns. To adopt new technology usually means to abandon an older technology and destroy old human capital, which is not easy because old firms' vintage capital is directly tied with their current practices, organizational and human capital. Moreover, the manager of an old firm may lack of knowledge to know new methods or may not have the necessary skills to implement it. In contrast, young firms will have more incentive to adopt new frontier methods because

[2] In the model, price of risk is countercyclical.

[3] An incomplete list of papers including Cochrane 1991, Titman, Wei and Xie 2004, Cooper, Gulen and Schill 2007, Polk and Sapienza 2008, Xing 2009, etc, document that investment and expected returns are negatively related.

they are not burdened with old vintage technology. For example, Hobijn and Jovanovic (2001) document that it is the new firms rather than incumbents that bring in the new technology after the IT revolution in 1970's. In addition, as is demonstrated in Jovanovic and Rosseau (2001, 2005), young firms are more likely to adopt the new vintage capital as ideas and products associated with the latest technology are often brought to market by new firms. Hence, firm age serves a good empirical counterpart for technology adoption, implying that young firms should earn lower expected returns than old firms. Consistent with the model prediction, we find that young firms earn lower average returns than old firms in the U.S. publicly traded companies.[4] A spread portfolio of stocks that goes long on young firms and short on old firms generates a significant value-weighted spread of 2.85% per annum. In addition, we find that firm age and investment are closely related: Investing firms on average are younger than less investing firms. This new finding suggests that both firm age and capital investment are important in characterizing the expected returns. In standard asset pricing tests, we find that the unconditional CAPM is unable to explain the cross-sectional variation in the returns of five age portfolios, because the spread in the market beta is too small across these portfolios. The Fama and French (1993) three factor model cannot capture the variation in the returns of these portfolios either.

The model also provides a fresh explanation for the value premium which is different from the existing literature. In the model, value firms are loaded with the old vintage machines and are much further away from the technology frontier than growth firms. Costly technology adoption prevents value firms from smoothing their dividend streams when facing aggregate risk, particularly in economic downturns. Thus value firms' dividends covary more with aggregate uncertainty and hence are riskier than growth firms. Notably the value premium in our model hinges on costly technological adoption, which differs from Zhang (2005) who work through capital adjustment costs. On the other hand, the interaction between optimal technology adoption and vintage capital reinforces the mechanism emphasized in Zhang (2005) who demonstrates that costly reversibility of capital is one of key mechanisms driving

[4] Zhang (2006) and Jiang, Lee and Zhang (2005) document the similar finding regarding firm age and the expected returns, but they attribute their findings to information uncertainty and behaviour bias, respectively.

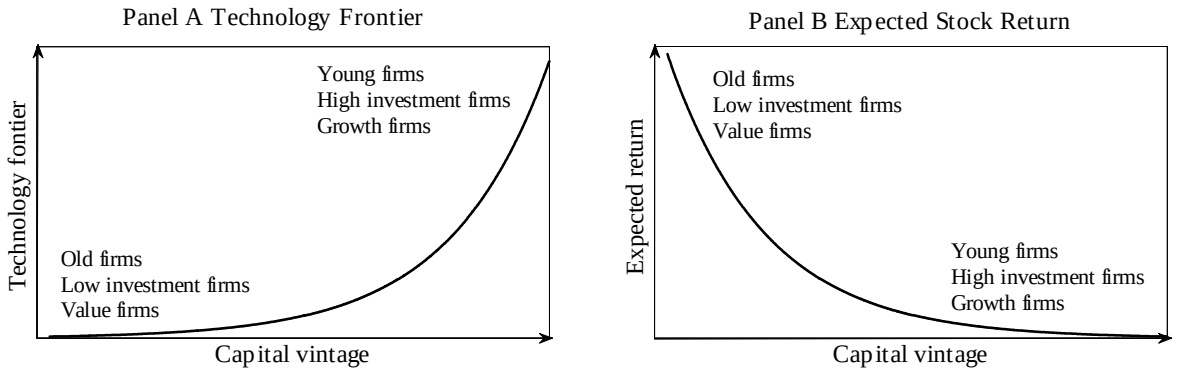


Figure 1: **Technology Frontier and Expected Return**

This figure plots the distribution of firms on technology frontier with the related characteristics and expected returns implied by the model. In panel A, technology frontier grows as capital evolves from the old vintage to the new vintage. In panel B, expected returns decrease in capital vintage evolution.

the value premium. Moreover, we find that value firms on average are older than growth firms and the value spread in increasing in firm age in the data. These new findings not only confirm the model predictions, but also shed light on the relationship between firm life cycle characteristic, vintage capital and the value premium.

Finally, the model produces a series of refutable hypotheses for future empirical research: (i) Firms' vintage capital age and expected returns are negatively related; (ii) growth firms' capital age is smaller than that of value firms; and (iii) at the aggregate level, the adoption cycle (measured as the evolution of the number of firms adopting the latest technology over time) is negatively related to stock market returns.

Figure 1 summarizes the distribution of firms on the technology frontier with the related characteristics (panel A) and their expected returns in the model (panel B). Young firms, high investment firms and growth firms are distributed on the right upper and lower end in the panels A and B, respectively. These firms locate on the latest technology frontier and are associated with new vintage capital and low expected returns. In contrast, old firms, low investment firms, and value firms are distributed on the left lower and upper corner of the panels A and B, respectively. These firms operate the old vintage capital and earn high expected returns.

This paper is related to a growing pool of literature investigating the link between technological progress and stock prices (e.g., MacDonald 1994, Greenwood and Jovanovic

1999, Jovanovic and Stolyarov 2000, Jovanovic and Rousseau 2004, and Jermann and Quadrini 2005, etc). Most of these papers focus a great deal on innovation decisions while we study the link between vintage capital and asset returns. Notably, Albuquerque and Wang (2008) use investment specific technological change to examine asset pricing and welfare implications of imperfect investor protection at aggregate level. Our paper differs in that we study the implications of firms' technological adoption in asset prices and returns. Pastor and Veronesi (2009) investigate technological revolutions and aggregate stock prices movement by focusing on the uncertainty of technological revolutions as the driving force for the stock price "bubbles". We differ because we concentrate on the relationship between firm level adoption of the latest vintage capital and stock prices.

Our work is related to a strand of literature of production-based asset pricing models focusing on capital investment and expected returns.[5] We differs in that we study the effect of firms' technological adoption of latest vintage capital on risk and expected returns. The model generates a discrete decision rule for investment which is different from the existing literature using convex adjustment cost which implies a continuous investment.

# 2 The Model

The economy is comprised of a continuum of firms that produce a homogeneous product. Firms behave competitively, taking the product price as given.

## 2.1 Production Technology

Production requires capital and is subject to aggregate productivity and firm-specific productivity shocks. The aggregate productivity, $x_t$, has a stationary and monotone Markov transition function, $Q_x(x_{t+1}|x_t)$, and is given by:

$$x_{t+1} = \bar{x}(1-\rho_x) + \rho_x x_t + \sigma_x e_{t+1} \tag{1}$$

[5] An incomplete list includes Cochrane 1991, Berk, Green and Naik 1999, Carlson, Fisher and Giammarino 2004, Zhang 2005, Belo 2006, Liu, Whited and Zhang 2008, Li, Livdan and Zhang 2009, Bazdresch, Belo and Lin (2009), etc.

where $e_{t+1}$ is an IID standard normal shock.

The firm-specific productivity for firm $j$, $z_t^j$, has a common stationary and monotone Markov transition function, $Q_z(z_{t+1}^j|z_t^j)$, given by:

$$z_{t+1}^j = \rho_z z_t^j + \sigma_z \epsilon_{t+1}^j \tag{2}$$

in which $\epsilon_{t+1}^j$ is an IID standard normal shock and $\varepsilon_{t+1}^i$ and $\varepsilon_{t+1}^j$ for any pair $(i, j)$ with $i \neq j$. Moreover, $e_{t+1}$ is independent of $\varepsilon_{t+1}^j$ for all $j$. In the model, the aggregate productivity shock is the driving force of time-series economic fluctuations and systematic risk, and the firm-specific productivity shock is the driving force of the cross-sectional heterogeneity of firms.

The production function is given by

$$Y_t^j = e^{x_t + z_t^j} (K_t^j)^\alpha \tag{3}$$

in which $Y_t^j$ and $K_t^j$ are the output and capital of firm $j$ at time $t$, respectively. The production function is decreasing returns to scale with $0 < \alpha < 1$.

## 2.2 Costly Technology Adoption

Technology frontier, denoted by $N_t$, represents the stock of general and scientific technology. Following Parente and Prescott (1994) and Cooper, Haltiwanger and Power (1999), we assume that the technology frontier $N_t$ grows at a constant rate of $\gamma > 0$. Thus,

$$N_{t+1} = (1 + \gamma) N_t. \tag{4}$$

All firms have access to this technology frontier, but it is costly to adopt. Given the state of uncertainty, $\left(x_t, z_t^j\right)$, and the level of technology, $N_t$, the firm chooses between adopting the latest technology, $N_{t+1}$, and continue using the existing vintage capital, $K_t^j$, for another period. Hence the capital stock for firm $j$ evolves as follows:

$$K_{t+1}^{j} = \begin{cases} (1-\delta)\, K_t^j & \text{if} \quad \phi_t^j = 0 \\ N_{t+1} & \text{if} \quad \phi_t^j = 1 \end{cases}, \tag{5}$$

where $\delta$ is the rate of depreciation for capital. The choice variable in this problem is $\phi_t^j$ where $\phi_t^j = 1$ means that new technology is adopted in period $t$ and the existing vintage capital is replaced. Accordingly, investment is given by

$$I_t^j = \begin{cases} 0 & \text{if} \quad \phi_t^j = 0 \\ N_{t+1} - (1-\delta)\, K_t^j & \text{if} \quad \phi_t^j = 1 \end{cases}. \tag{6}$$

Equation (6) implies an inaction for investment when the firm chooses not to adopt the latest technology and an investment spike when the firm does. As a result, investment lumpiness arises in the model. Equation (6) also implies that investment is irreversible when $\phi_t^j = 0$.

The gain of technology adoption is that the new vintage is more productive than old vintage as it reflects the current technological progress. Technology adoption incurs a cost $C_t^j$ given by

$$C_t^j = \begin{cases} F_t^N & \text{if} \quad \phi_t^j = 0 \\ F_t^A + I_t^j + \frac{c}{2}\frac{I_t^{j2}}{K_t^j} & \text{if} \quad \phi_t^j = 1 \end{cases} \tag{7}$$

in which $F_t^A$ is the fixed cost of technology adoption, and the quadratic term $\frac{c}{2}\frac{I_t^{j2}}{K_t^j}$ is the capital adjustment cost. Here, the fixed cost $F_t^A$ captures the cost of learning new technology, workers training costs, etc. When no adoption occurs, the firm incurs a fixed cost of production denoted as $F_t^N$.

## 2.3 Pricing Kernel

Following Berk, Green and Naik (1999) and Zhang (2005), we directly specify the pricing kernel without explicitly modelling the consumer's problem. The pricing kernel is given by

$$\log m_{t,t+1} = \log \beta + \gamma_t (x_t - x_{t+1}) \tag{8}$$

$$\gamma_t = \gamma_0 + \gamma_1 (x_t - \bar{x}) \ , \tag{9}$$

where $m_{t,t+1}$ denotes the stochastic discount factor from time $t$ to $t+1$. The parameters $\{\beta, \gamma_0, \gamma_1\}$ are constants satisfying $1 > \beta > 0$, $\gamma_0 > 0$ and $\gamma_1 < 0$.

In particular, following Zhang (2005), we assume in equation (9) that $\gamma_t$ is time varying and decreases in the demeaned aggregate productivity shock $x_t - \bar{x}$ to capture the countercyclical price of risk with $\gamma_1 < 0$.

## 2.4 Value Maximization

Let $V(K_t^j, x_t, z_t^j)$ denote the *cum*-dividend market value of equity for firm $j$. Define:

$$D_t^j \equiv Y_t^j - C_t^j \tag{10}$$

to be the distributions to shareholders. Let us define the following stationary variables:[6]

$$\left\{ v_t^j, d_t^j, y_t^j, k_t^j, i_t^j, f^A, f^N \right\} = \left\{ \frac{V_t^j}{N_t}, \frac{D_t^j}{N_t}, \frac{Y_t^j}{N_t}, \frac{K_t^j}{N_t}, \frac{I_t^j}{N_t}, \frac{F_t^A}{N_t}, \frac{F_t^N}{N_t} \right\}.$$

Then equation (5) can be rewritten as

$$k_{t+1}^j = \begin{cases} \theta k_t^j & \text{if} \quad \phi_t^j = 0 \\ 1 & \text{if} \quad \phi_t^j = 1 \end{cases} \tag{11}$$

where $\theta = \frac{(1-\delta)}{\mu}$ is the obsolescence due to technology progress.

[6] Note $i_t = \frac{K_{t+1}^j - (1-\delta) K_t^j}{N_t} = (1+\gamma)\, k_{t+1}^j - (1-\delta)\, k_t^j$ if $\phi_t^j = 1$.

The dynamic value-maximizing problem for firm $j$ is:

$$v\left(k_t^j, x_t, z_t^j\right) = \max_{\{\phi_t^j\}} \left\{v^A\left(k_t^j, x_t, z_t^j\right), v^N\left(k_t^j, x_t, z_t^j\right)\right\}, \tag{12}$$

where $v^A\left(k_t^j, x_t, z_t^j\right)$ is the firm value when new technology is adopted with the superscript "A" referring to adoption:

$$v^A\left(k_t^j, x_t, z_t^j\right) = y_t^j - f^A - i_t^j - \frac{c}{2}\frac{i_t^{j2}}{k_t^j} + \mathbb{E}_t m_{t,t+1} v\left(1, x_t, z_t^j\right),$$

and $v^N\left(k_t^j, x_t, z_t^j\right)$ is the firm value when new technology is not adopted with the superscript "N" denoting non-adoption,

$$v^N\left(k_t^j, x_t, z_t^j\right) = y_t^j - f^N + \mathbb{E}_t m_{t,t+1} v\left(\theta k_t^j, x_t, z_t^j\right).$$

## 2.5 Risk and Expected Stock Return

In the model, risk and expected stock returns are determined endogenously along with firms' value-maximization. Evaluating the value function in equation (12) at the optimum,

$$\begin{aligned} v\left(k_t^j, x_t, z_t^j\right) &= d_t^j + \mathbb{E}_t\left[m_{t,t+1} v(k_{t+1}^j, x_{t+1}, z_{t+1}^j)\right] &(13)\\ \Rightarrow\ 1 &= \mathbb{E}_t\left[m_{t,t+1} r_{t+1}^j\right] &(14)\end{aligned}$$

where equation (13) is the Bellman equation for the value function and equation (14) follows from the standard formula for stock return $r_{t+1}^j = v(k_{t+1}^j, x_{t+1}, z_{j,t+1}) / \left[v\left(k_t^j, x_t, z_t^j\right) - d_t^j\right]$. Note that if we define $p_t^j \equiv v\left(k_t^j, x_t, z_t^j\right) - d_t^j$ as the *ex*-dividend market value of equity, $r_{t+1}^j$ reduces to the usual definition, $r_{t+1}^j \equiv \left(p_{t+1}^j + d_{t+1}^j\right)/p_t^j$.

Now we rewrite equation (14) as the beta-pricing form, following Cochrane (2001 p. 19):

$$\mathbb{E}_t\left[r_{t+1}^j\right] = r_{ft} + \beta_t^j \zeta_{mt} \tag{15}$$

where $r_{ft} \equiv \frac{1}{\mathbb{E}_t[M_{t,t+1}]}$ is the real interest rate, and $\beta_t$ is the risk defined as:

$$\beta_t^j \equiv \frac{-Cov_t\left[r_{t+1}^j, m_{t,t+1}\right]}{Var_t\left[m_{t,t+1}\right]} \tag{16}$$

and $\zeta_{mt}$ is the price of risk defined as

$$\zeta_{mt} \equiv \frac{Var_t\left[m_{t,t+1}\right]}{E_t\left[m_{t,t+1}\right]}.$$

Equation (15) and (16) imply that risk and expected returns are endogenously determined along with optimal adoption decisions. All the endogenous variables are functions of three state variables (the endogenous state variable, $k_t^j$ and two exogenous state variables, $x_t$ and $z_t^j$), which can be solved numerically.

# 3 Properties of Model Solutions

## 3.1 Calibration

We calibrate the model in annual frequency. Table 1 summarizes the benchmark parameter values.

[Insert Table 1 here.]

We set the curvature parameter in the production function, $\alpha$, to be 0.7, roughly consistent with the average of the estimates in Cooper and Ejarque (2001, 2003) and Cooper and Haltiwanger (2006). The capital depreciation rate $\delta = 10\%$ is from Jermann (1998). We set persistence $\rho_x = 0.98^4$ and conditional volatility $\sigma_x = 0.007 * 2$. These annual values correspond to quarterly values of 0.98 and 0.007, respectively, as in King and Rebelo (1999). The long-run average level of aggregate productivity, $\bar{x}$, is a scaling variable. We set the average long-run capital in the economy at 0.5, which implies that the long-run average of aggregate productivity $\bar{x} = -0.90$. To calibrate persistence $\rho_z$ and conditional volatility $\sigma_z$ of firm-specific productivity, we follow Gomes (2001) and Zhang (2005) and restrict these

two parameters using their implications on the degree of dispersion in the cross-sectional distribution of firms' stock return volatilities. Thus $\rho_z = 0.79$, and $\sigma_z = 0.18$, which implies an average annual volatility of individual stock returns of 20%, approximately the average of 25% reported by Campbell at al (2001).

Following Zhang (2005), we pin down the three parameters governing the stochastic discount factor, $\beta, \gamma_0$, and $\gamma_1$ to match three aggregate return moments: the average real interest rate, the volatility of the real interest rate, and the average annual Sharpe ratio. This procedure yields $\beta = 0.94$, $\gamma_0 = 28$, and $\gamma_1 = -300$, which generate an average annual real interest rate of 1.65%, an annual volatility of real interest rate of 4.8%, an average annual Sharpe ratio of the model of 0.32, which are similar to those in the data.

We set the growth rate of technological frontier $\gamma = 0.032$, consistent with the estimate in Greenwood, Hercotwiz and Krusell (1997).[7] We set the fixed cost of adoption, $f^A = 0.3$, and the quadratic cost of adoption, $c = 0.1$ to match the firm level investment rate volatility of 26% annually. We set the fixed cost of production with no adoption, $f^N = 0.1$ such that the average market-to-book ratio in the model is 1.93, which is roughly close to the data. Table 2 reports the data moments and the model-implied moments.

[Insert Table 2 ]

## 3.2 Properties of the Model Solution

Using the benchmark parametrization, we discuss how the key endogenous variables such as the *cum*-dividend and *ex*-dividend firm value, investment, and conditional beta are determined by the underlying state variables.

### 3.2.1 Value Functions and Policy Functions

Panels A, B and C in Figure 2 plot the variables against $k_t^j$ and $x_t$, with $z_t^j$ fixed at their long-run average level of zero. Panels D, E and F in Figure 2 plot the variables against $k_t^j$

[7] I choose to calibrate the growth rate $\gamma$ as that of the investment specific technological change, but the notion of the technology frontier in the model is broader than the investment specific technological change in Greenwood et al (1997). The quantitative implication of the model does not vary with the different values of the growth rate $\gamma$.

and $z_t^j$, with $x_t$ fixed at their long-run average level $\bar{x}$. Each one of these panels has a set of curves corresponding to different values of $x_t$ or $z_t^j$ and the arrow in each panel indicates the direction along which $x_t$ or $z_t^j$ increases.

In Panels A and D in Figure 2, the firms' technological adoption decision, $\phi_t^j$, is more likely to occur when the aggregate productivity is high, and firms with higher firm-specific productivity or small capital stock are more likely to adopt.[8] In Panels B and E in Figure 2, the firms' *cum*-dividend market value of equity is increasing in the aggregate productivity, the firm-specific productivity and the capital stock. More productive firms and larger firms have higher market value of equity, consistent with Li, Livdan and Zhang (2009). In Panels C and F in Figure 2, the firms' *ex*-dividend market value of equity is increasing in the aggregate productivity and the firm-specific productivity, but is not monotonically increasing in capital stock because the optimal adoption decision $\phi_t^j$ is not monotone in capital. Combining panels A, C, D, and F, we find that all else being equal, technology adopting firms' *ex*-dividend market value of equity is higher than those of non-adopting firms, consistent with Jovanovic and Rosseau (2005).

[Insert Figure 2 here]

In Panels A and D of Figure 3, the optimal investment $i_t^j$ is decreasing in capital stock, indicating that smaller firms grow faster which is consistent with Evans (1987). Adopting firms with less capital invest more and grow faster than non-adopting firms that do not invest. Note that the optimal investment $i_t^j$ is not continuous in capital $k_t^j$ because the optimal adoption decision $\phi_t^j$ is a discrete choice variable. This prediction is in contrast with the Q-theory of investment which implies a smooth investment continuous in capital (e.g., Hayashi 1982). In Panels B and E of Figure 3, adopting firms use the latest vintage capital while non-adopting firms use their existing vintage capital.

[Insert Figure 3 here]

[8] Recall that $\phi_t^j$ is an indicator variable which takes unity when technological adoption occurs and zero otherwise.

### 3.2.2 Risk and Expected Return

In panels E and F of Figure 3, the firms' expected stock return $\mathbb{E}_t\left[r^j_{t+1}\right]$ and conditional beta $\beta^j_t$ are decreasing in the firm-specific productivity, indicating that more productive firms are less risky, which is consistent with Li, Livdan and Zhang (2009). Combining the optimal adoption decision $\phi^j_t$ in panel A of Figure 2, all else being equal, the expected returns and conditional betas of adopting firms are smaller than those of non-adopting firms. As noted, costly technology adoption plays a key role in generating the risk dispersion between adopting firms and non-adopting firms. In the model, the risk of a firm is negatively related to its flexibility in adopting the latest vintage capital to smooth its dividends when facing aggregate uncertainty. Technology adoption cost is the offsetting force of dividend smoothing mechanism. Adopting firms are more flexible in dividend smoothing, and hence are less risky than non-adopting firms.

# 4 Quantitative Analysis

Here, the quantitative implications concerning the cross section of returns in the model are investigated. We simulate 100 samples each with 3500 firms and each firm has 50 annual observations. The empirical procedure on each artificial sample is implemented and the cross-simulation results are reported. We then compare model moments with where possible those in the data (See Appendix A1 for data construction).

## 4.1 Investment and Technology Adoption

In the model, adopting frontier technology requires investing in the latest vintage capital, which gives rise to an one-to-one mapping between technology adoption and capital investment. This relation implies that investment-intensive firms should earn lower expected returns than firms investing less in capital.

We test this prediction following the empirical procedure in Xing (2009) in constructing 10 value-weighted portfolios sorted on investment.[9] We sort all firms into 10 portfolios based

[9] Given that there is no distinction between different capital vintage in the data, I use capital expenditure

on firms' rate of investment, $i^j_{t-1}/k^j_{t-1}$, in ascending order as of the beginning of year $t$. We construct an investment-spread portfolio long in the low $i^j_{t-1}/k^j_{t-1}$ portfolio and short in the high $i^j_{t-1}/k^j_{t-1}$ portfolio, for each simulated panel. Panel A in Table 3 reports the average stock returns of 10 portfolios sorted on investment in the data, and panel B reports the model implied moments. Consistent with Xing (2009), firms with low $i^j_{t-1}/k^j_{t-1}$ on average earn higher stock returns than firms with high $i^j_{t-1}/k^j_{t-1}$ in the model. The model-implied average value-weighted investment-spread is 3.85% per annum. This spread is short of magnitude to the data, 12.74%.

In order to investigate if the spread in the average returns across these portfolios reflects a compensation for risk, at least as measured by traditional risk factors, we conduct standard time series asset pricing tests to both the real and simulated data using the CAPM and the Fama-French (1993) three factor model as the benchmark asset pricing models. In testing the CAPM, we run time series regressions of the excess returns of these portfolios on the market excess return portfolio while in testing the Fama-French three factor model we run time series regressions of the excess returns of these portfolios on the market excess return portfolio (Market), and on the SMB (small minus big) and HML (high minus low) factors. We find that the model also replicates reasonably well the portfolio results in terms the failure of the unconditional CAPM, and the relative better fit of the Fama and French (1993) three factor model.

To further test the model prediction that technological change is favourable to young firms and renders old vintage capital obsolete, we examine the average age of 10 investment portfolios. Following Jovanovic and Rosseau (2001, 2005), firm age is identified as the number of months since the firms appear on the Center for Research in Securities Prices (CRSP). Firms with low $i^j_{t-1}/k^j_{t-1}$ on average are older than firms with high $i^j_{t-1}/k^j_{t-1}$. The average age difference between the high investment and low investment portfolios is more than 60 months. In the model, there is no direct counterpart for firm age. Instead, we use the average capital age, the time from the last technology adoption till the current period, $t$. In the simulated data, firms with low $i^j_{t-1}/k^j_{t-1}$ on average have higher capital age than firms

(Compustat data 128) scaled by property, plant and equipment (data 8) to measure rate of investment.

with high $i_{t-1}^j/k_{t-1}^j$.

[Insert Table 3 here]

## 4.2 Firm Age and Technology Adoption

As noted, firm age and technology adoption are positively related as young firms are more likely to adopt the new vintage capital, demonstrated in Hobijn and Jovanovic (2001) and Jovanovic and Rosseau (2001, 2005). Hence, young firms should be less risky and earn lower expected returns than old firms.

To test this prediction, we construct 5 value-weighted age portfolios in the data. We sort all firms into 5 portfolios based on firms' age in ascending order as of the beginning of year $t$. We then calculate the value-weighted annual average stock excess returns for each age portfolio. Panels A in Table 4 report the data moments.

[Insert Table 4 here]

From Panel A in Table 4, consistent with the model prediction, young firms on average earn lower average stock returns than old firms. The age spread (the return difference between old firms and young firms) is 2.85% per annum. This age spread cannot be captured by either the CAPM and Fama-French 3 factor model. In Panel B in Table 4, we sort simulated firms on firm capital age. The model generates a reliable age spread, which is 2.02% per annum, close to that in the data, 2.85%. The model replicates the failure of the CAPM model in explaining the age spread, and Fama-French 3 factor model does a better job in capturing the age spread in the model.

### 4.2.1 Age Premium

Here we investigate the economic mechanism in the model for generating a sizable capital age premium. Since firm age and technology adoption are positively related, this analysis can also shed light on the economic mechanism for the firm age premium.[10] Our quantitative

[10]In principal, capital age and firm age are not exactly the same, but empirical studies suggest that they are closely related: Young firms tend to use new vintage capital and hence their capital age is smaller than old firms.

results show that costly technology adoption is the key driving force. Table 5 reports the comparative statics of the age premium across different parametrizations. When technology adoption is cost-free, $f^A = 0$, age spread is close to zero. The intuition is the following: In good times, both young firms and old firms can take the advantage of the positive aggregate shock, so they both covary with aggregate risk, meaning that their risk difference is low. In bad times, young firms with positive firm-specific shock either adopt the latest technology incurring a fixed cost or they have already upgraded their capital to the technology frontier. As a result, young firms are able to smooth their dividend streams using their productive capital. However old firms cannot upgrade their old vintage because it is too costly for them (with unproductive capital stock, their operating income is low in bad times). So their dividend streams covary more with economic downturns than do young firms, and hence are riskier. With $f^A = 0$, both young firms and old firms can adopt the new technology freely to smooth dividends facing bad aggregate shock, implying a tiny risk dispersion. Fixed production cost, $f^N$, and quadratic adoption cost, $\frac{c}{2}\frac{i^2}{k}$, are both quantitatively important in generating the difference in the expected returns across the age portfolios, but with a secondary effect.

[Insert Table 5 here]

## 4.3 The Value Premium

### 4.3.1 One Way Sort

Here, we explore the relation between technological adoption and the value premium.

First we investigate if the model can generate a positive relation between the book-to-market ratio and expected stock returns. We construct 10 value-weighted book-to-market portfolios. The book value of a firm in the model is identified as its capital stock. We sort all firms into 10 portfolios based on firms' book-to-market ratio, $k^j_{t-1}/p^j_{t-1}$, in ascending order as of the beginning of year $t$. We construct a value-spread portfolio long in the high book-to-market portfolio and short in the low book-to-market portfolio for each simulated panel. Table 6 reports the average stock returns of 10 portfolios sorted by book-to-market ratio.

Consistent with the findings of Fama-French (1992, 1993), firms with low book-to-market ratios earn lower stock returns on average than do firms with high book-to-market ratios. The model-implied average value-weighted value-spread is 8.84% per annum. This spread is close to that documented in the data, 8.72%. Moreover, we find that growth firms on average are younger and invent more than value firms, implying that growth firms on average are more frequently adopting the latest vintage capital, consistent with the model prediction.

### 4.3.2 Comparative Statics

We then investigate the mechanism driving the value premium. Both fixed technology adoption cost, $f^A$, and the fixed production cost without adoption, $f^N$, are critical. The mechanism driving the value premium is as follows: In good times, both growth firms and value firms can use their capital to smooth their dividend streams when facing the favourable economic conditions. So they all covary with aggregate risk and their risk disparity is low. In bad times, growth firms are equipped with the latest vintage capital which are more productive than those of value firms. Value firms are loaded with old vintage capital and are unable to adopt the latest technology because it is too costly for them. Hence, they have to use the old vintage machine which depreciate faster as new technology renders them obsolete. In addition, the implied investment irreversibility in equation (6) prevents value firms from disinvesting to smooth dividends. As a result, growth firms are more flexible in smoothing their dividend streams than value firms, particularly in economic downturns, implying that value firms are riskier than growth firms.

[Insert Table 6 here]

### 4.3.3 Vintage Capital and the Value Premium

Here we investigate the relation between vintage capital and the value spread. In the model, value firms are further away from the technology frontier than growth firms, hence the risk dispersion between value firms and growth firms is in increasing firms' vintage capital age. As noted, firm age and vintage capital (technology adoption) are directly linked, we explore this

prediction using firm age in the data. We first sort all firms in Compustat into three portfolios based on firms' book-to-market ratio, $k^j_{t-1}/p^j_{t-1}$, in ascending order as of the beginning of year $t$. Meanwhile we sort all firms into three portfolios based on firm age in ascending order as of the beginning of year $t$. The intersections give nine portfolios sorted on book-to-market and firm age. We construct value-spread portfolios long in the high book-to-market portfolio and short in the low book-to-market portfolio given each firm age portfolio. Panels A and B in Table 7 reports the average stock returns of nine portfolios in the data and implied by the model, respectively.

The sorting procedure generates an impressive spread in the average excess returns of these portfolios. For example, the high book-to-market and high age portfolio (high-high) has a value weighted excess return of 14.17% in the data whereas the low book-to-market and low age portfolio (low-low) has a value weighted excess return of only 8.46%, implying a difference of 5.71% per year. This finding is consistent with the model prediction: Value spread increases in firm age. Moreover the model generates a reliable spread between high-high and low-low portfolios of 5.94% per year, close to the data.

We also conduct standard asset pricing tests on these nine portfolios. The unconditional CAPM is clearly rejected on these portfolios both in the real and simulated data, because the spread in the market betas (not reported) is too small relative to the spread in the realized average excess returns. As a result, the model generates large statistically significant alphas.

[Insert Table 7 here ]

The test results for the Fama and French (1993) model presented in Table 7 confirm the better fit of this model, as in the real data. The alphas between high-high and low-low portfolio is not statistically significant.

# 5 Summary and Future Work

We study the relationship between technology adoption and expected stock returns in a dynamic vintage capital model. Our results suggest that technology adoption is an important

determinant of the cross section of returns. In our setting, technology adopting firms are less risky than non-adopting firms because costly technology adoption restricts the degree of flexibility of non-adopting firms in smoothing their dividend streams. We use capital investment to identify technological adoption decisions, and find the empirical results are consistent with the model prediction: In the U.S. publicly traded firms, investing firms earn lower stock returns than less-investing firms. Moreover, the positive relation between firm age and expected returns is also supportive to the model prediction, as technological change destroys old vintage capital and favours young firms. By linking technological adoption to the differences between value firms and growth firms, the model also sheds light on the value premium and the evolution of firms' vintage capital.

Future research can proceed in a few directions. First, in our setup, we assume adopting new technology renders old vintage capital completely obsolete and worthless. One can extend the current framework to allow for a resale market for old capital to better capture investment dynamics. Second, for simplicity, we assume that firms' capital stock are of the same size when adopting the frontier technology following Parente and Prescott (1994) and Cooper, Haltiwanger and Power (1999). A richer model with different size of vintage capital can follow Greenwood and Yorukoglu (1997) and Cooley, Greenwood and Yorukoglu (1997). Lastly, the relations between firms' plant-level decisions and the expected stock returns is also worth investigating. Firms' establishment level data has been extensively studied in the investment literature (e.g., Caballero and Engel 1993, 1994 and 1999, Caballero, Engel and Haltiwanger 1997, Cooper and Haltiwanger 2006, etc). Examining the relationship between plant investment, employment, age, etc., and asset returns would open up new avenues for empirical research, and provide new insight for the driving forces of the cross section of returns.

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# Appendix

## A1 Data

Monthly stock returns are from the CRSP and accounting information is from the CRSP/COMPUSTAT Merged Annual Industrial Files. The sample is from July 1971 to June 2006. We exclude from the sample any firm-year observation with missing data or for which total assets, the gross capital stock, or total employees are either zero or negative. In addition, as standard, we omit firms whose primary SIC classification is between 4900 and 4999 (regulated firms) or between 6000 and 6999 (financial firms). Following Vuolteenaho (2002) and Xing (2008), we require that a firm must have a December fiscal-year end in order to align the accounting data across firms. Since most firms have a December fiscal-year end, this selection requirement does not bias the representativeness of the sample. Finally, following Fama and French (1993), we also require that each firm must have at least two years of data to be included in the sample.

We construct the key variables as follows. Firm level capital investment $i_t$ is given by COMPUSTAT data item 128 (Capital Expenditures). The capital stock $k_t$ is given by the data item 8 (Property, Plant and Equipment). Firm age is defined as the number of months after a firm appears in CRSP; following Fama and French (1993), we define book value of equity as the Compustat book value of common equity (data item 60) plus balance-sheet deferred taxes (data item 74) and investment tax credits (data item 208), minus the book value of preferred stock. Depending on availability, we use the redemption (data item 56), liquidation (data item 10), or par value (data item 130) of preferred stock. When data item 60 is not available, the liquidation value of common equity (data item 235) is used. COMPUSTAT data item 128 is used for capital investment, $i$; the net book value of property, plant, and equipment (data item 8) is used for the capital, $k$; the investment rate is given by the ratio of investment to beginning of the period capital stock ($i_t/k_t$) (as in Xing (2008)); Book-to-market equity is the ratio of the book value of equity to the market value of equity; market equity is price times shares outstanding at the end of December of t, from CRSP; size is the price times shares outstanding at the end of June of year t, from CRSP. The data

for the three Fama-French factors (SMB, HML and Market excess returns), the six Fama-French factors and the risk-free rate is from Prof. Kenneth French's webpage. See Fama and French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," Journal of Financial Economics, for a complete description of these factor returns.

## A2 Numerical Algorithm

To solve the model numerically, we use the value function iteration procedure to solve the firm's maximization problem. The value function and the optimal decision rule are solved on a grid in a discrete state space. We specify a grid with 10000 equi-distanced points for the capital with upper bounds kmax=1.

The state variable $x$ is defined on continuous state space, which has to be transformed into discrete state space. Because both aggregate and idiosyncratic productivity processes are highly persistent, we use the method described in Rouwenhorst (1995). The method of Tauchen and Hussey (1991) does not work well when persistence level is above 0.9. We use 11 grid points for the $x$ process and 21 grid points for the $z$ process. In all cases the results are robust to finer grids as well. Once the discrete state space is available, the conditional expectation can be carried out simply as a matrix multiplication. Finally, we use a simple discrete, global search routine in maximizing problems.

Table 1:
**Parameter Values under Benchmark Calibration**

This table presents the calibrated parameter values of the benchmark model.

| Parameter | Value | Description |
|---|---|---|
| Preferences | | |
| $\beta$ | 1.06 | Subjective discount factor |
| $\gamma_0$ | 28 | Constant price of risk |
| $\gamma_1$ | -300 | Time-varying price of risk |
| | | |
| Technology | | |
| $\alpha$ | 0.70 | Production function curvature |
| $\delta$ | 10% | Rate of depreciation |
| $\gamma$ | 0.032 | Growth rate of technology frontier |
| | | |
| Adoption Costs | | |
| $f^A$ | 0.3 | Fixed cost of technology adoption |
| $c$ | 0.1 | Size of quadratic cost of technology adoption |
| $f^N$ | 0.1 | Fixed production cost without technology adoption |
| | | |
| Productivity Shocks | | |
| $\bar{x}$ | -0.90 | Long run average of aggregate productivity |
| $\rho_x$ | $0.98^4$ | Persistence of aggregate production |
| $\sigma_x$ | 0.014 | Conditional volatility of aggregate productivity |
| $\rho_z$ | 0.79 | Persistence of firm-specific productivity |
| $\sigma_z$ | 0.18 | Conditional volatility of firm-specific productivity |

Table 2:

**Unconditional Moments under the Benchmark Calibration**

This table presents the selected moments in the data and implied by the model under the benchmark calibration. The simulated results is based on 100 artificial panel with 3500 firms and 50 periods of data. We report the cross-simulation averaged annual moments. The data moments are estimated from a sample from 1971 to 2006.

| Moments | Data | Benchmark Model |
|---|---|---|
| The average annual risk-free rate | 0.022 | 0.028 |
| The annual volatility of risk-free rate | 0.029 | 0.042 |
| The average annual Sharpe ratio | 0.39 | 0.32 |
| The average annual rate of investment | 0.33 | 0.16 |
| The volatility of annual rate of investment | 0.25 | 0.26 |
| The average annual market to book ratio | 1.49 | 1.93 |
| The volatility of annual of market to book ratio | 0.23 | 0.40 |

Table 3:
**Average Returns of Investment Portfolios**

This table reports the CAPM and the Fama-French three factor model asset pricing test results on ten value-weighted portfolios sorted on investment-to-capital ratio. The table reports the intercept of a time series regression of the portfolio excess returns on the market excess return (if CAPM) or the Market, SMB and HML factors (if Fama–French three factor model (1993)), the corresponding t-statistics with Newey-West standard errors in parenthesis, and the factor betas. The reported statistics are averages from 100 samples of simulated data, each with 3500 firms and 50 annual observations.

| | Data | CAPM $\alpha$ | t-statisitics | Fama-French $\alpha$ | t-statisitics | Age (Month) |
|---|---|---|---|---|---|---|
| Panel A: Data | | | | | | |
| Low | 15.45 | 9.54 | 3.17 | 4.96 | 2.43 | 156 |
| 2 | 12.81 | 6.83 | 2.95 | 2.01 | 1.64 | 194 |
| 3 | 12.69 | 7.00 | 3.53 | 2.70 | 2.56 | 210 |
| 4 | 11.86 | 5.93 | 3.23 | 2.13 | 2.1 | 212 |
| 5 | 12.17 | 6.08 | 3.17 | 2.67 | 2.47 | 210 |
| 6 | 11.62 | 5.30 | 2.95 | 2.23 | 2.33 | 200 |
| 7 | 9.72 | 3.12 | 1.5 | 0.92 | 0.72 | 180 |
| 8 | 8.91 | 2.10 | 0.96 | 0.21 | 0.16 | 154 |
| 9 | 8.38 | 0.68 | 0.27 | -0.17 | -0.1 | 121 |
| High | 2.71 | -5.80 | -1.88 | -5.37 | -2.64 | 90 |
| Low-High | 12.74 | 15.34 | 6.7 | 10.33 | 4.9 | 66 |
| Panel B: Model | | | | | | |
| Low | 10.47 | 0.90 | 7.09 | 0.23 | 2.45 | 70 |
| 2 | 10.45 | 0.87 | 6.48 | 0.17 | 0.08 | 71 |
| 3 | 10.47 | 0.86 | 6.90 | 0.14 | -0.45 | 71 |
| 4 | 10.35 | 0.78 | 5.79 | 0.24 | 2.98 | 72 |
| 5 | 10.21 | 0.68 | 5.11 | 0.33 | 2.13 | 73 |
| 6 | 10.10 | 0.56 | 4.21 | 0.32 | 2.27 | 73 |
| 7 | 9.69 | 0.17 | 1.03 | 0.15 | 1.07 | 70 |
| 8 | 8.48 | -0.79 | 3.54 | -0.13 | -1.71 | 66 |
| 9 | 7.21 | -1.36 | 17.91 | -0.59 | -3.68 | 56 |
| High | 6.62 | -1.45 | -4.08 | -0.69 | -3.20 | 43 |
| Low-High | 3.85 | 2.35 | 11.49 | 0.92 | 6.16 | 27 |

Table 4:
**Average Returns of Firm Age Portfolios**

This table reports the CAPM and the Fama-French three factor model asset pricing test results on five value weighted portfolios sorted on firm age (in the data, on Panel A) and capital age (in the simulated data, on Panel B). The table reports the intercept of a time series regression of the portfolio excess returns on the market excess return (if CAPM) or the Market, SMB and HML factors (if Fama–French three factor model (1993)), the corresponding t-statistics with Newey-West standard errors in parenthesis, and the factor betas. The reported statistics are averages from 100 samples of simulated data, each with 3500 firms and 50 annual observations.

| | Return | CAPM $\alpha$ | t-statisitics | Fama-French $\alpha$ | t-statisitics |
|---|---|---|---|---|---|
| Panel A: Data | | | | | |
| Young | 3.64 | -4.88 | -2.33 | -2.83 | -1.64 |
| 2 | 5.32 | -2.48 | -1.25 | -1.55 | -0.83 |
| 3 | 6.34 | -1.44 | -1.04 | -1.02 | -0.76 |
| 4 | 7.07 | 0.02 | 0.02 | 0.13 | 0.13 |
| Old | 6.50 | 0.71 | 0.93 | 0.52 | 0.8 |
| Old - Young | 2.85 | 5.60 | 2.29 | 3.35 | 1.85 |
| Panel B: Model | | | | | |
| Young | 4.93 | -0.66 | -0.37 | -0.31 | -1.27 |
| 2 | 6.57 | 0.36 | 5.02 | 0.58 | 4.23 |
| 3 | 6.69 | 0.20 | 3.24 | -0.15 | -1.01 |
| 4 | 6.77 | 0.10 | 4.00 | -0.12 | -0.67 |
| Old | 6.96 | 0.17 | 0.39 | -0.12 | -0.65 |
| Old - Young | 2.02 | 0.82 | 3.33 | 0.20 | 0.49 |

Table 5:
**Comparative Statics of Age Portfolios**

This table reports the value-weighted excess stock returns of five portfolios sorted on firm age (in the data) and capital age (in the model). Data is from Ken French's website. The High-Low variable is the return difference between the highest age portfolio and the lowest age portfolio. The sample period is from 1971 to 2006. We simulate 100 artificial panels, each of which has 3600 firms and each firms has 50 annual observations. We perform the empirical analysis on each simulated panel and report the cross-simulation average results. All returns are in percentages.

| | Data | Benchmark Model | Zero Adoption Cost $f^A = 0$ | Zero Fixed Cost $f^N = 0$ | Zero Quadratic Adoption Cost $c = 0$ |
|---|---|---|---|---|---|
| Young | 3.64 | 4.93 | 5.56 | 5.99 | 7.11 |
| 2 | 5.32 | 6.57 | 5.57 | 6.85 | 7.81 |
| 3 | 6.34 | 6.69 | 5.57 | 6.88 | 8.06 |
| 4 | 7.07 | 6.77 | 5.58 | 6.96 | 8.22 |
| Old | 6.50 | 6.96 | 5.57 | 7.02 | 8.32 |
| Old - Young | 2.85 | 2.02 | 0.01 | 1.03 | 1.21 |

Table 6:
**Average Returns of Book-to-Market Portfolios**

This table reports the value-weighted excess stock returns of ten portfolios sorted on book-to-market ratio. Data is from Ken French's website. The High-Low variable is the return difference between the highest book-to-market decile and the lowest book-to-market decile. The sample period is from 1971 to 2006. We simulate 100 artificial panels, each of which has 3500 firms and each firms has 50 observations. We perform the empirical analysis on each simulated panel and report the cross-simulation average results. All returns are in percentages.

| | Data | Benchmark Model | Zero Adoption Cost $f^A = 0$ | Zero Fixed Cost $f^N = 0$ | Zero Quadratic Adoption Cost $c = 0$ | Firm Age Data | Capital Age Model |
|---|---|---|---|---|---|---|---|
| Low | 7.98 | 5.05 | 5.22 | 7.69 | 6.42 | 105 | 48 |
| 2 | 10.76 | 5.52 | 5.40 | 7.38 | 7.00 | 126 | 60 |
| 3 | 11.41 | 5.85 | 5.45 | 7.21 | 7.28 | 147 | 65 |
| 4 | 12.53 | 6.07 | 5.53 | 7.01 | 7.53 | 160 | 67 |
| 5 | 11.92 | 6.28 | 5.55 | 6.83 | 7.89 | 168 | 67 |
| 6 | 12.24 | 6.66 | 5.63 | 6.69 | 8.19 | 180 | 68 |
| 7 | 13.82 | 7.02 | 5.66 | 6.49 | 8.48 | 181 | 69 |
| 8 | 13.03 | 7.56 | 5.71 | 6.25 | 9.23 | 180 | 71 |
| 9 | 14.51 | 8.67 | 5.78 | 6.04 | 10.43 | 174 | 72 |
| High | 16.70 | 13.89 | 5.92 | 5.99 | 16.02 | 156 | 79 |
| High-Low | 8.72 | 8.84 | 0.70 | -1.70 | 9.59 | 51 | 31 |

Table 7:
**Nine Portfolios Double Sorted on Book-to-Market and Firm Age**

This table reports the CAPM and the Fama-French three factor model asset pricing test results on nine value-weighted portfolios double sorted on book-to-market ratio and firm age (in the data, on Panel A) and (capital age in the simulated data, on panel B). The table reports the intercept of a time series regression of the portfolio excess returns on the market excess return (if CAPM) or the Market, SMB and HML factors (if Fama–French three factor model (1993)), the corresponding t-statistics with Newey-West standard errors in parenthesis, and the factor betas. The reported statistics are averages from 100 samples of simulated data, each with 3500 firms and 50 annual observations.

| Characteristics | | Excess Return | CAPM $\alpha$ | t-statisitics | Fama-French $\alpha$ | t-statisitics |
|---|---|---|---|---|---|---|
| BM | AGE | | | Panel A: Data | | |
| Low | Low | 8.46 | -7.79 | -3.14 | -3.00 | -1.65 |
| Low | Mid | 8.54 | -3.44 | -1.74 | -5.78 | -3.2 |
| Low | High | 11.27 | 2.17 | 1.13 | -1.29 | -0.72 |
| Mid | Low | 8.52 | -4.60 | -2.63 | -1.10 | -0.72 |
| Mid | Mid | 15.34 | 3.93 | 2.33 | 0.80 | 0.56 |
| Mid | High | 16.91 | 6.13 | 3.43 | 0.98 | 0.74 |
| High | Low | 9.11 | -0.55 | -0.57 | 1.30 | 1.59 |
| High | Mid | 10.85 | 1.98 | 1.68 | -0.14 | -0.12 |
| High | High | 14.17 | 4.84 | 2.5 | -1.13 | -0.83 |
| HH - LL | | 5.71 | 12.62 | 3.58 | 1.87 | 0.98 |
| | | | | Panel B: Model | | |
| Low | Low | 3.60 | -0.53 | -2.07 | 0.16 | 1.33 |
| Low | Mid | 4.47 | -0.16 | 1.93 | -0.15 | -1.17 |
| Low | High | 4.59 | -0.13 | 1.15 | -0.03 | -0.17 |
| Mid | Low | 4.81 | -0.14 | -2.88 | 0.38 | 2.21 |
| Mid | Mid | 5.76 | 0.27 | 2.13 | -0.20 | -1.62 |
| Mid | High | 5.74 | 0.14 | 1.68 | 0.07 | 0.52 |
| High | Low | 8.33 | 1.15 | -1.94 | 0.41 | 1.32 |
| High | Mid | 9.76 | 1.92 | 1.79 | 0.20 | 0.67 |
| High | High | 9.54 | 1.60 | -0.11 | -0.45 | -1.55 |
| HH - LL | | 5.94 | 2.13 | 0.76 | -0.62 | -1.71 |

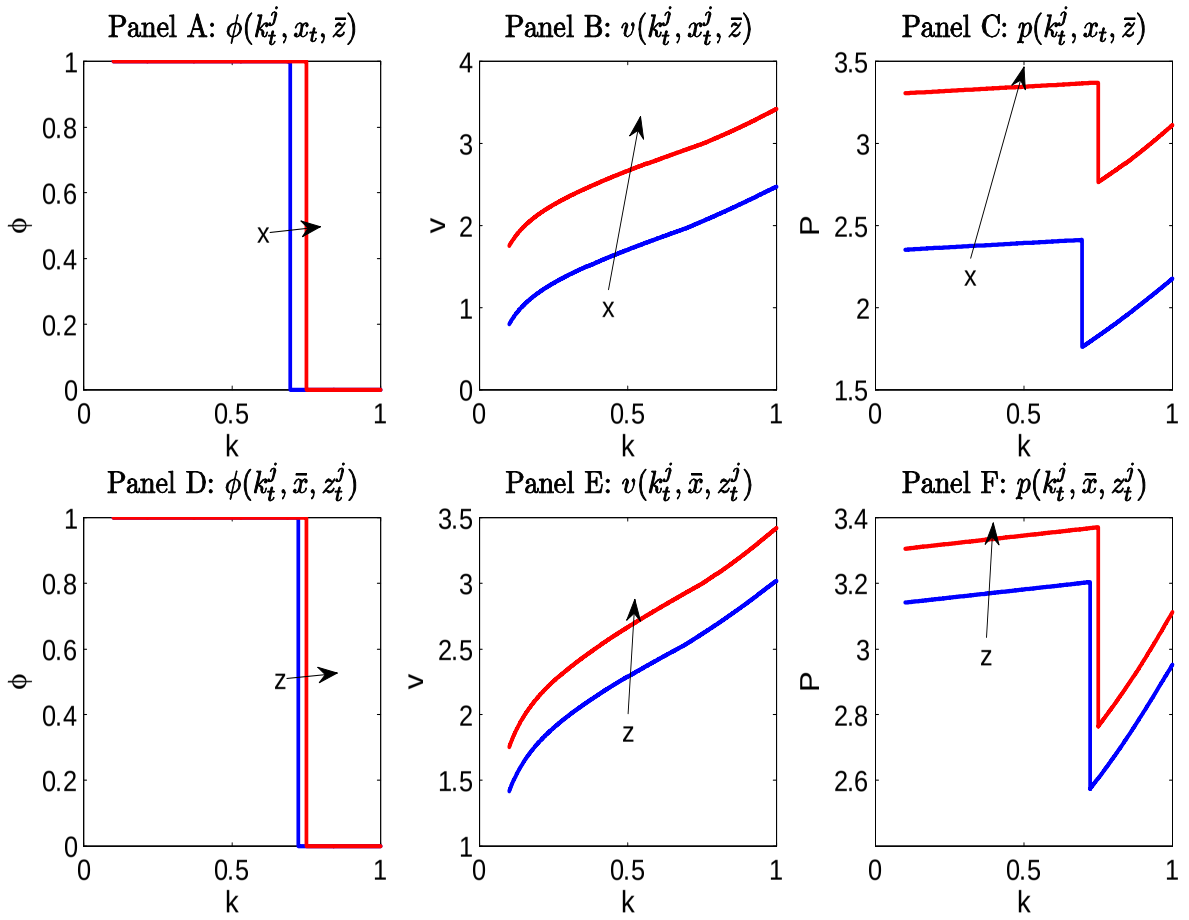


Figure 2: **The Policy Functions, Value Functions and Ex-Dividend Firm Value against the Underlying States**

This figure plots the policy functions ($\phi\left(k_t^j, x_t, z_t^j\right)$, panels A and D), the value functions ($v\left(k_t^j, x_t, z_t^j\right)$, panels B and E) and the ex-dividend stock price ($p\left(k_t^j, x_t, z_t^j\right)$, panels C and F) against the three state variables. We fix the firm-specific productivity $z_t^j$ at its long-run average level of zero in panels A, B and C. We fix the aggregate productivity $x_t$ at its long-run average level of $\bar{x}$ in panels D, E and F. Each one of these panels has a set of curves corresponding to different values of $x_t$ or $z_t^j$ and the arrow in each panel indicates the direction along which $x_t$ or $z_t^j$ increases.

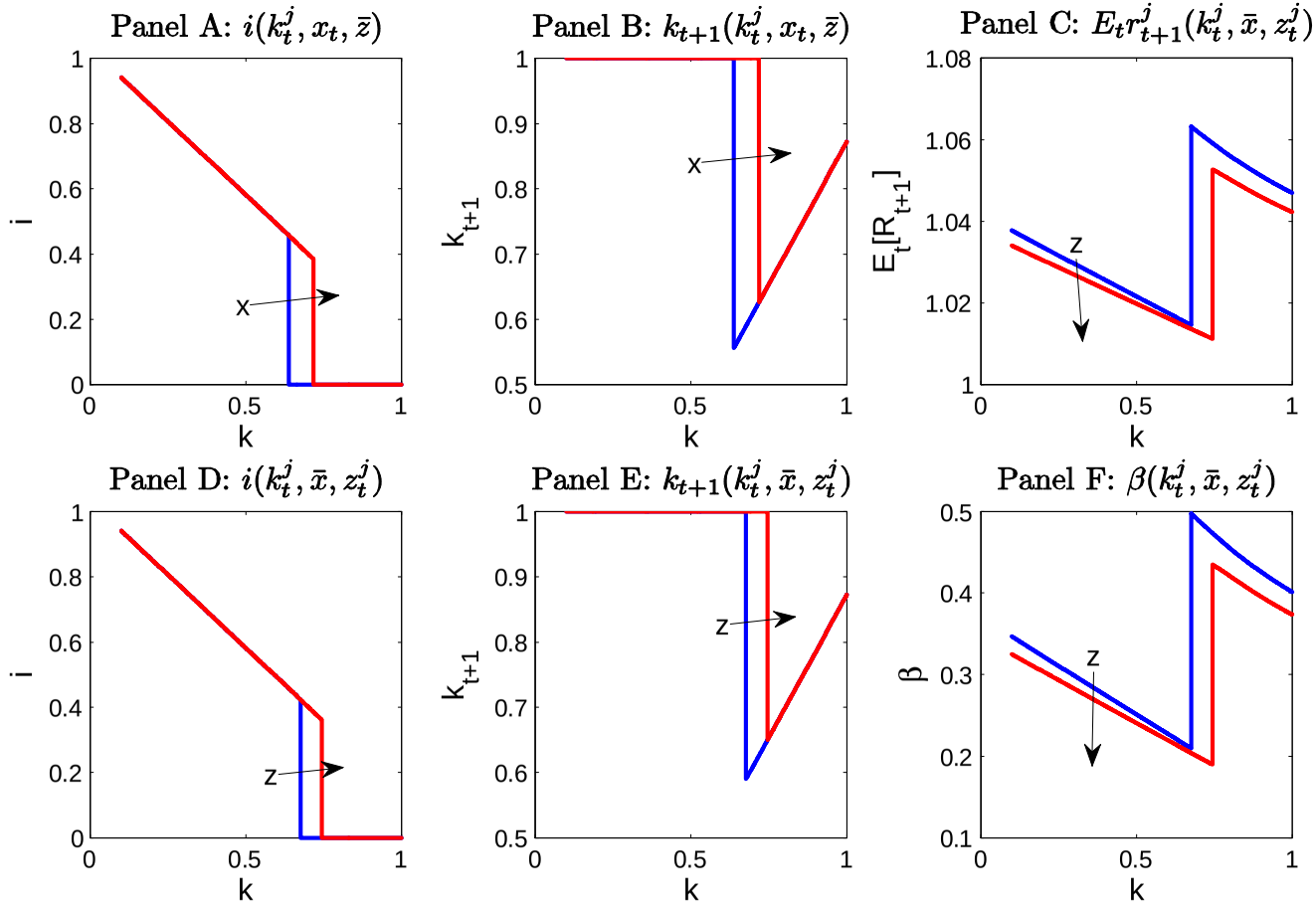


Figure 3: **The Optimal Investment, Capital, Expected Return and Conditional Beta against the Underlying States**

This figure plots the optimal investment ($i\left(k_t^j, x_t, z_t^j\right)$, panels A and D), the optimal capital ($k_{t+1}\left(k_t^j, x_t, z_t^j\right)$, panels B and D), the expected return ($\mathbb{E}_t\left[r_{t+1}^s\left(k_t^j, x_t, z_t^j\right)\right]$, panel C) and the conditional beta ($\beta_t\left(k_t^j, x_t, z_t^j\right)$, panel F) against the three state variables. We fix the firm-specific productivity $z_t^j$ at its long-run average level of zero in panels A and B. We fix the aggregate productivity $x_t$ at its long-run average level of $\bar{x}$ in panels B, D, E and F. Each one of these panels has a set of curves corresponding to different values of $x_t$ or $z_t^j$ and the arrow in each panel indicates the direction along which $x_t$ or $z_t^j$ increases.