The risks of old age: Asset pricing implications of technology adoption*

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Abstract

We study the impact of the technological change on asset prices in a dynamic model economy that features a stochastic technology frontier and costly technology adoption. Firms adopt the latest technology embodied in new capital to reach the stochastic technology frontier, but this decision entails an adoption cost. The model predicts that firms operating with old capital are more risky and hence offer higher expected returns than firms using young capital. This is because old capital firms are more likely to upgrade their capital in the near future and hence are more exposed to shocks driving the technology frontier. Our empirical analyses support the model's predictions. We find an annual return spread of 9% between old and young capital firms. The standard asset pricing models fail to explain this return spread, while a measure of technology adoption shocks prices well the capital age portfolios.

JEL Classification: E23, E44, G12

Keywords: Technology adoption, technology frontier shock, vintage capital, investment, capital age, stock returns

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1 Introduction

Over the last few decades, the nature of economic growth and productivity advancement has transformed profoundly: technological changes taking the form of adopting the new and more productive capital goods—especially in information and communication equipment and software—have represented the major source of output growth in the United States (Jorgenson (2001)). Productivity growth embodied in new capital has accelerated significantly over the past 30 years, from 2 percent per year in the 1960s to 4.5 percent in the 1990s (Gordon (1990) and Cummins and Violante (2002)). In this paper, we study the impact of the time-variation of the aggregate technology frontier on firms' asset prices and real quantities. We show that firms' decisions in adopting the frontier technology have a significant impact on the cross sectional expected stock returns.

We develop a dynamic model that features a stochastic technology frontier and costly technology adoption, similar in spirit to Abel and Eberly (2012). In our model, the technology frontier, which all firms have access to, follows a stochastic process driven by a systematic shock. Facing this shock and the standard aggregate and firm-specific productivity shocks, firms decide to adopt the latest capital, which is more efficient, or to keep operating with the existing capital which will become obsolete (i.e., less productive) over time. In the model, firms incur a cost when adopting the latest technology. The more advanced the new technology is relative to the firms' current capital technology, the less firms' current technology can be used to the operation of the new technology and the more costs the firms will need to incur if they choose to adopt the more advanced technology. However, the benefit is that the more advanced the new technology is, the more efficient the capital is. Adoption costs arise because not all firms' existing expertise (human capital or workers' skills) can be applied to the new technology. This cost consists of two parts: a linear variable cost and a fixed adoption cost. In particular, the fixed adoption cost delays the adoption decision of firms (especially firms with relatively new capital and high productivity). On the other hand, because of the linear costs, the further a firm's installed capital is from the technology frontier, the more costly the adoption of the latest capital. The model implies that unproductive firms, rather than upgrading their capital, keep using their vintage capital until the capital becomes obsolete. The benefit of adopting the latest capital is a more productive installed capital. Thus, firms trade-off the cost of adoption and the benefit of more efficient technology embodied in the new capital. Costly technology adoption restrict firms' flexibilities in upgrading their capital stock to the technology frontier, giving rise to the risk dispersion between technology-adopting firms and non-adopting firms.

By linking vintage capital to firm risk, the model sheds light on the relationship between firms' capital age and expected returns. The key insight of the model is that firms that adopt the latest technology or operate with the new capital are less risky than non-adopting firms. In the model, technology adopting firms are firms with young capital age and growth firms. Thus the model provides a novel prediction for the cross sectional variations of stock returns associated with capital age and book-to-market ratios. These predictions are distinct from the standard investment-based asset pricing models where capital vintage is homogeneous across firms and there is no distinction between new and old capital.

The economic mechanism for the model's results is as follows. For adopting firms, the new capital installed has already been upgraded with the latest technology. After a positive productivity shock, the adopting firms will delay further investment because of the fixed adoption cost. Hence, their continuation value is less exposed to the fluctuations of the technology frontier or equivalently, to the technology frontier's shock. In contrast, non-adopting firms are more likely to upgrade their capital in the near future if they face a positive productivity shock. Therefore, their continuation value is more affected by the technology frontier shock. Thus, adopting firms with young capital age are less risky with lower expected returns than non-adopting firms with high capital age. In addition to generating a capital age premium, the model also provides a novel explanation for the value premium. Value firms in the model are non-adopting firms with low productivity. Because upgrading to the latest technology frontier is costly, they have to operate with their obsolescent vintage capital which is far less efficient than the technology frontier. Growth firms are productive firms that are able to catch up the latest technology. This allows them to better able to smooth their dividend streams. As a result, value firms are more risky than growth firms.

Through several comparative static exercises, we show that the existence of technology adoption costs is important for the model to capture the cross sectional return spreads. In particular, without adoption costs, the model generates age and value spreads that are much smaller than the benchmark model and the data counterparts. Furthermore, the average capital age in the zero technology adoption specification also drops substantially. This happens because all firms can adopt the frontier technology freely, thus reducing the cross sectional risk dispersion and resulting in a counterfactually too young capital age on average in the economy.

Empirically, we estimate the firm' capital age by using firm–level investment data of the U.S. public companies following the industrial organization literature (e.g., Salvanes and Tveteras 2004). Given that firms' capital age is not directly observable in the data, our measure of capital age provides a new firm characteristics that allows us to test the model predictions. We show that firms with young capital age earn lower average returns than the firms with old capital age. In particular, a spread portfolio of stocks that goes long on old capital age firms and short on young capital age firms generates a significant spread of 9% (value-weighted) and 15% (equal–weighted) per annum. In firm-level regressions, we show that the capital age predictability for the future returns remains significant after controlling for well-known return predictors in the literature including investment, size, book–to–market, and return on equity.

Furthermore, we show that the unconditional capital asset pricing model (CAPM) cannot explain the capital age return spread in the data. The sensitivity of the returns of firms with different capital age to the aggregate stock market factor (market risk) is negatively correlated with its average stock returns – the reverse of what the CAPM needs to explain the capital age return spread. As a result, the CAPM-implied pricing error of the capital age return spread is larger than the capital age return spread itself. The model replicates this finding, thus providing an economic explanation for the failure of the CAPM. According to the model, the aggregate stock market is mostly driven by the standard aggregate productivity shock, and thus it is weakly correlated with the aggregate technology frontier shock, which is the main driver of the capital age return spread in the cross section. Finally, other standard asset pricing factor models such as the Fama-French five factors and Hou-Xue-Zhang four factor model cannot explain the capital age spread as well.

In the last part of the paper, we propose a measure of the technology frontiers shock based on the introduction of new technology standards. In particular, we follow Baron and Schmidt (2017) and use the number of technology standards released by both US and international standard setting organizations (SSOs) to capture the adoption of new technologies. Our results show that our measure is (1) able to price the capital age sorted portfolios, (2) is a significantly priced source of risk when we use a variety of test portfolios, and (3) it is not subsumed by other macroeconomic shocks related to the cross-section of equity returns. Overall, the data points toward technology adoption shocks as a source of systematic risk that is priced in the economy.

Related literature This paper is related to a growing pool of literature investigating the link between technological progress and stock prices[1]. 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 the literature of production-based asset pricing models which focus on links between capital investment and expected returns (e.g., Zhang, (2005), Belo and Yu (2013), Imrohoroglu and Tuzel (2014) among many others). We differ from these papers in that in our model, capital vintage and efficiency are no longer homogeneous over time and across firms, thus technology adoption directly affects firms' risk and expected returns.

The empirical industrial organization literature shows that technology embodied in new capital (i.e., capital age) and a firm's age show little comovement (Dunne (1994)) and relies on methodologies based on firm-level investment behavior to estimate a firm's capital vintage (e.g., Mairesse (1978), Hulten (1991) and Salvanes and Tveteras (2004)). We contribute to this literature by estimating capital age for a large set of U.S. publicly traded companies and studying its asset pricing implications.

[1] An incomplete list includes Jovanovic and MacDonald (1994), Greenwood and Jovanovic (1999), Jovanovic and Rousseau (2001), Laitner and Stolyarov (2003), Albuquerque and Wang (2008), Papanikalaou (2011), Jermann and Quadrini (2012), Garleanu, Panageas, and Yu (2012), Garleanu, Kogan, and Panageas (2012), Kogan and Papanikalaou (2014), among many others.

2 The model

In this section, we present a parsimonious dynamic model with a stochastic technology frontier and costly technological adoption to study the relationship between vintage capital and asset returns.

2.1 Production technology

Firms use their physical capital (K_t) to produce a homogeneous good (Y_t) while facing an aggregate productivity shock (X_t) and a firm-specific productivity shock ($Z_{j,t}$). To save on notation, we omit firm index j whenever possible. The production function is given by:

$$Y_t = X_t Z_t K_t, \tag{1}$$

in which X_t is aggregate productivity and Z_t is firm-specific productivity. The production function exhibits constant returns to scale.

Aggregate productivity follows a random walk process with a drift

$$\Delta x_{t+1} = g_x + \sigma_x \varepsilon^x_{t+1}, \tag{2}$$

in which $x_{t+1} = \log(X_{t+1})$, Δ is the first-difference operator, ε^x_{t+1} is an i.i.d. standard normal shock, and μ_x and σ_x are the average growth rate and conditional volatility of aggregate productivity, respectively.

Firm-specific productivity follows the AR(1) process

$$z_{t+1} = \bar{z}(1 - \rho_z) + \rho_z z_t + \sigma_z \varepsilon^z_{t+1}, \tag{3}$$

in which $z_{t+1} = \log(Z_{t+1})$, ε^z_{t+1} is an i.i.d. standard normal shock that is uncorrelated across all firms in the economy and independent of ε^x_{t+1}, and $\bar{z}$, ρ_z, and σ_z are the mean, autocorrelation, and conditional volatility of firm-specific productivity, respectively.

2.2 Costly technology adoption

We denote the stock of general and scientific technology of the entire economy with N_t. Following Parente and Prescott (1994), Greenwood and Yorukoglu (1997), and Cooper, Haltiwanger, and Power (1999), we assume that the technology frontier N_t grows at an i.i.d. stochastic rate,

$$N_{t+1} = N_t e^{g_N + \sigma_N \eta_t}, \tag{4}$$

where g_N is the average log growth rate and σ_N is the volatility. η_t denotes an i.i.d standard normal random variable. The timing of η_t and the technology frontier is slightly different from the productivity shocks. The technology frontier at $t+1$ is determined by the shock (η_t) at t so that there is no uncertainty in the investment cost of adopting the technology frontier at t. Note that gross investment at t depends on N_{t+1} if a firm chooses to adopt the technology frontier.

Given the productivity shocks (x_t, z_t) and the level of technology, N_t, the firm chooses between adopting the latest technology, N_{t+1}, or continue operating on the existing vintage capital, K_t, for another period. Hence the capital stock for the firm evolves as follows:

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

where δ is the rate of depreciation for capital. The choice variable in this model is ϕ_t where $\phi_t = 1$ means that new technology is adopted in period t and the existing vintage capital is replaced; and $\phi_t = 0$ means that the firm continue operating the existing old capital. Accordingly, gross investment is given by

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

The gain of technology adoption is that the new capital is more efficient than old vintage as it reflects the current technological progress. This can be seen in an extreme case by comparing two series of capital over time: $\{N_0, N_1, N_2, ..., N_t\}$ and $\left\{N_0, (1-\delta) N_0, (1-\delta)^2 N_0, ..., (1-\delta)^t N_{0,}\right\}$. The first series represents the case where the firm adopts the latest technology every period and is able to stay on the technology frontier in the entire history, whereas the second case represents another case where the firm is unable to adopt the latest technology and remains operating the old vintage capital all the time. As the technology frontier evolves over time, the capital of the firm in the first case is on average more productive in terms of efficiency unit (units of output to be produced) than the capital in the second case which is effectively obsolete. For example, at t, the expected capital of the first firm is $\mathrm{E}[N_t] = e^{g_N t + \frac{1}{2}\sigma_N^2 t} N_0$, which can be an order of magnitude more efficient than the capital of the second firm, $(1-\delta)^t N_0$, when t is large.

All firms can adopt the latest technology vintage, but it is costly to do so. We assume that technology adoption entails an investment cost C_t given by

$$C_t = \begin{cases} 0 & \text{if} \quad \phi_t = 0 \\ f_i X_t K_t + X_t I_t & \text{if} \quad \phi_t = 1 \end{cases} . \tag{7}$$

The investment cost per unit of investment (X_t) varies over time and it is driven by aggregate productivity as in Jermann (1988) and Eisfeldt and Papanikolaou (2013). Other than the stochastic unit cost, the investment costs consists of two parts: a fixed cost ($f_i K_t$) and a linear variable cost (I_t). Here, the fixed cost (as in Cooper Haltiwanger, and Power 1999)captures the cost of learning new technology, workers training costs, and the cost of abandoning old capital. It could also include the cost in the destruction of old organizational capital or human capital of existing workers who are used to the old vintage capital.

The fixed investment cost in equation (7) causes asyncronous technology adoption as in Jovanovic and Stolyarov (2000). A technology frontier shock does not induce firms with the same technology efficiency to adopt the latest capital vintage at the same time. Depending on the level of the firm-specific productivity, more productive firms decide to innovate, while less productive firms find the adoption decision too costly and keep operating with the existing capital vintage. This leads to firms' heterogeneity in technical efficiency.

Finally, firms' dividend D_t is given by

$$D_t = Y_t - C_t - f_o X_t N_t,$$

where $f_o X_t N_t$ is a fixed operating cost.[2]

2.3 Firms' problem

The firm takes as given the stochastic discount factor $M_{t,t+1}$ used to value the cash flows arriving in period $t+1$. We specify the log stochastic discount factor to be a function of the two aggregate shocks in the economy:

$$\log M_{t,t+1} = -r - \frac{1}{2}\lambda_e^2 - \frac{1}{2}\lambda_\eta^2 - \lambda_e e_{t+1} - \lambda_\eta \eta_{t+1}.$$

where r_f is the risk-free rate. The sign of the risk factor loading parameters (λ_e and λ_η) is positive, consistent with the empirical findings that times of technological progress are associated with an increase in consumption and output growth and hence are lower marginal utility states. The risk-free rate is set to be constant. This allows us to focus on risk premia as the main driver of the results in the model as well as to avoid parameter proliferation.

The firm maximizes shareholders' value by choosing to adopt the technology frontier ($\phi_t = 1$) or keep using its vintage capital ($\phi_t = 0$)

$$V(Z_t, K_t, X_t, N_t) = \max_{\phi_t} D_t + \mathrm{E}_t[M_{t,t+1} V(Z_{t+1}, K_{t+1}, X_{t+1}, N_{t+1})].$$

Since both aggregate productivity and the technology frontier follow random walk processes, the firm's problem is non-stationary. We show how to obtain a detrended version of the model economy in the Appendix (Section A1).

[2] We assume that the fixed production costs grow at the same rate as the economy to be on the balanced growth path.

2.4 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 at the optimum, we obtain

$$V_t = D_t + \mathrm{E}_t \left[M_{t,t+1} V_{t+1} \right] \tag{8}$$

$$\Rightarrow \quad 1 = \mathrm{E}_t \left[M_{t,t+1} R_{t+1} \right], \tag{9}$$

where equation (8) is the Bellman equation for the value function and equation (9) follows from the standard formula for stock return $R_{t+1} = V_{t+1} / \left[V_t - D_t \right]$. Note that if we define $P_t \equiv V_t - D_t$ as the *ex*-dividend market value of equity, R_{t+1} reduces to the common definition of stock return, $R_{t+1} \equiv \left(P_{t+1} + D_{t+1} \right) / P_t$.

Following Cochrane (2001 p. 19), we rewrite equation (9) as the beta-pricing form

$$\mathrm{E}_t \left[R_{t+1} \right] - r = \beta_e \lambda_e + \beta_\eta \lambda_\eta, \tag{10}$$

where $r = -\log(\mathrm{E}\left[M_{t,t+1} \right])$ is the real interest rate. $\beta = (\beta_e, \beta_\eta)$ denotes the vector of the quantities of risk and it is defined as:

$$\beta = -\frac{\mathrm{Cov}_t \left[R_{t+1}, M_{t,t+1} \right]}{\mathrm{Var}_t \left[M_{t,t+1} \right]}. \tag{11}$$

In the model, the prices of risks are exogenously specified in the pricing kernel. However, the model is able to generate cross–sectional dispersion in risk premia due to the heterogeneity in the quantities of risk (β).

3 Model results

In this section we discuss the solution and the calibration of the model. After detrending, all the endogenous variables are functions of three state variables: (i) the endogenous capital k_t; (ii) the firm–level productivity z_t; and (iii) the technology shock η_t. Because the functional forms are not available analytically, we solve for these functions numerically. Appendix A1 detrends the model. Appendix A2 provides a description of the solution algorithm (value function iteration) and the numerical implementation of the model.

The model is solved at a quarterly frequency to be consistent with the frequency of capital age in the data. To neutralize the impact of the initial condition, we simulate a panel of $5,000$ firms for 1000 quarters to generate a stationary cross sectional distribution of firms. Each firm is characterized by the firm–level state variables z_t and k_t. Then, using this distribution of firms as initial condition, we simulate 100 panels of artificial data with sample size of 120 quarters and $5,000$ firms. We aggregate quarterly variables to annual and report the cross-sample average results.

Table 1 reports the parameter values used in the baseline calibration. The model is calibrated using parameter values reported in previous studies, whenever possible, or by matching a set of empirical moments. Table 2 reports the model–generated moments together with their empirical counterparts. Because we do not explicitly target the cross section of return spreads in the baseline calibration, we use these moments to evaluate the model in Section 3.3.

3.1 Calibration

Stochastic processes: We set the annual average log growth of the technological frontier ($4g_N$) equal to 0.0138, consistent with the estimate in Greenwood, Hercowitz and Krusell (1997).[3] In the model, the aggregate productivity shock x_t is essentially a profitability shock. We set the annual average log growth of aggregate productivity ($4g_x$) equal to 0.012 to match the average growth of aggregate profits and the quarterly volatility of the aggregate productivity shock to be $\sigma_x = 0.078$ to match the volatility of aggregate profits. In the data, we measure aggregate profits using data from the National Income and Product Accounts (NIPA). Given the volatility of the aggregate productivity shock, we set the volatility of log technology frontier to $\sigma_N = 0.095$. The long-run average of firm-specific productivity, $\bar{z}$, is a scaling variable, which determines the long-run average productivity of the representative firms. We set $\bar{z} = -1.5$ which implies that the average physical capital scaled by the technology frontier (k_t) across firms is around 0.75. To calibrate the persistence ρ_z and conditional volatility σ_z of firm-specific productivity, we restrict

[3]We choose to calibrate the growth rate g_N 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 implications of the model remain unchanged with different values of the growth rate g_N.

these two parameters using their implications on the degree of dispersion in the cross-sectional distribution of firms' stock return volatilities. We set $\rho_z = 0.97^3$ following Zhang (2005), and set $\sigma_z = 0.21$, which implies an average annual volatility of individual stock returns of 30%, consistent with Campbell at al (2001).

Firm's technology: The quarterly capital depreciation rate (δ) is set to 0.03 as in Jermann (1998). The fixed cost of technology adoption (f_i) is the key parameter that drives the adoption frequency in the model. The higher the fixed cost of adoption, the lower the adoption frequency and hence the longer the average capital age. We set the fixed cost of technology adoption, $f_i = 3.4$, to match the average capital age (about 20 quarters) in the data. The fixed operating cost (f_o) drives the operating leverage of the firm in the model. It mainly affects the cross-sectional correlation between capital age and book-to-market ratio, average capital-to-market equity ratio, and the value premium. We set $f_o = 0.076$ to match the cross sectional correlation between capital age and book-to-market ratio of 0.2 in the data. Additionally the model implied average capital-to-market equity ratio is 0.3, close to the data.

Pricing kernel: The annual real risk-free rate is chosen to match the data $4r = 0.022$. We set the price of aggregate risk to be $\lambda_e = 3\sigma_x$ and the price the technology risk to be $\lambda_\eta = 4\sigma_N$ by matching average stock market return and the Sharpe ratio. This implies an annual market excess return of 6.5% and Sharpe ratio of 40%, values close to their empirical counterparts. These risk prices also imply an equivalent risk aversion parameter of 3 with respect to the aggregate productivity shock and an equivalent risk aversion parameter of 4 with respect to the technology frontier shock. Both are within reasonable range.

3.2 Properties of model solutions

Using the benchmark parametrization, we discuss the policy functions of interest such as the optimal investment and adoption decisions. Furthermore, we inspect the model predicted cross sectional stock returns by relating the model predicted stock risk premium and the state variables.

3.2.1 Value functions and policy functions

Figure 1 compares the optimal investment policies for high and low productivity (z) firms. Figure 2 compares the optimal adoption policy, the probability of adoption next year, the annual risk premium, the stock beta to the technology frontier shock (Beta_η), the book-to-market ratio (BM) and the ex-dividend firm value ($V - D$) for high and low productivity firms. All variables are detrended.

Panel A in Figure 1 plots the optimal capital next period (k_{t+1}) as a function of the capital this period (k_t). Panel B reports the corresponding investment rate which is defined as the ratio of investment over capital installed (I/K). The vintage of the installed capital plays a key role in shaping the technology adoption policies in the benchmark model.

First, high productivity firms (high z) optimally choose to adopt the technology frontier–which is represented as 1 for the detrended capital–when their technology is obsolete (low level of capital). Their investment rates are in general positive and declining in k, as shown in the bottom panel. In contrast, low productivity firms (low z) choose to keep operating with their obsolete capital and hence do not invest. Their investment rates are zero regardless of current capital level.

Second, high productivity firms optimally decide not to adopt the newest technology when their capital vintage is relatively recent. This is due to the fixed cost of investment in the model. These high productive firms, which have recently updated their capital stock, optimally choose to delay their adoption decision. These firms are characterized by high z and high capital k. This inaction region generates lumpy investment in our model, a feature we observe in the firm-level investment data. More importantly, this channel helps to generate a sizable number of firms with high capital age, as in the data. In a later section, we show that the model implied capital age drops significantly when removing this fixed investment cost.

Figure 2 depicts the optimal adoption policy, the probability of adoption next year, annual risk premium, stock beta to the technology frontier shock (Beta_η), the book-to-market ratio (BM) and the ex-dividend firm value ($V - D$) for high and low productivity (z) firms. The exogenous firm-specific productivity shock (z) generates heterogenous optimal adoption decisions across firms and hence endogenizes many interesting cross sectional patterns in firms' characteristics.

From Panel A in Figure 2, we can observe that given the same level of idiosyncratic productivity (z), firms with current capital lower than a certain threshold optimally choose to adopt the technology frontier (adoption $\phi = 1$). After adoption, a firm keeps operating with its current capital without any investment and hence its capital depreciates at a constant rate δ until next adoption. Panel B shows that the probability of adoption increases as capital depreciates. Only until the capital depreciates to the threshold, a firm adopts the latest technology frontier and hence the probability of adoption next year drops to zero due to the fixed adoption cost. This channel generates lumpy investment for a firm in the model.

More interestingly, Panels C and D show that the risk premium and stock beta to the technology frontier shock (Beta$_\eta$) as functions of capital and idiosyncratic productivity exhibit the same shape as the probability of adoption next year. This is because a firm's risk premium is driven by its exposure to the technology frontier shock which is determined by the probability of adopting the latest capital in the near future. This is also the key channel that allows the model to endogenously generate heterogeneity in cross sectional stock returns. In the model, young capital age firms are high k firms and old capital age firms are low k firms. From Panels B, C, and D, we can observe that old capital age firms are low k firms which tend to have a high adoption probability next year, and hence high exposure to the technology frontier shock (high Beta$_\eta$), and hence high expected returns.

Panels E shows that value firms (high book-to-market ratio) tend to be low k firms and low productive firms. Panels F shows that big firms measured by market equity $(V - D)$ tend to be high k firms and high productive firms.

3.2.2 Risk and expected return

After detrending the model, a stock return can be written as

$$R_{t+1} = \frac{V_{t+1}}{V_t - D_t} = \frac{v_{t+1}}{v_t - d_t} e^{g_N + \sigma_N \eta_t + \Delta x_{t+1}}. \tag{12}$$

Since both v_t and d_t are only functions of state variables (z_t, η_t, k_t), the first term $\frac{v_{t+1}}{v_t - d_t}$ does not depend on the aggregate productivity shock x_t. From Equation (12), the betas to aggregate productivity shock Δx_{t+1} across all the stocks equal to 1. By design, the aggregate productivity shock does not drive the cross sectional stock return but only drives the market return. We do this to emphasize the role played by the technology frontier shock in shaping the cross section of equity returns. This feature also allows the model to generate a failure of the the standard capital asset pricing model in capturing the cross sectional risk premia linked to the capital age spread and the book–to–market spread.

Figure 3 reports the betas to the aggregate productivity shock and the technology frontier shock across ten value weighted portfolio sorted on capital age in the benchmark model. The betas are estimated using the model simulated shocks and portfolio returns with a two factor model by time series regressions,

$$R^e_{j,t+1} = \alpha_j + \beta_{j,x}\Delta x_{t+1} + \beta_{j,\eta}\sigma_N \eta_{t+1}. \tag{13}$$

The beta to the aggregate productivity shock (β_x) equals to 1 across all the portfolios. As a consequence, cross–sectional differences in equity returns are not driven by different exposures to aggregate risk. More interestingly, the model implied beta to the technology frontier (β_η/σ_N) increases with capital age for both the value weighted and equal weighted portfolios. Stocks with older vintage capital load more on the technology frontier shock than stocks with younger vintage capital. With a constant positive price for the technology frontier risk, the model predicts that old capital stocks offer higher expected returns than young capital stocks.

3.3 Cross sectional stock returns

An important firm characteristic, which makes this model different from the standard investment-based model (e.g. Zhang (2005) and Papanikolaou (2011)) is capital age. The technology frontier represents the latest technology in capital and thus defines capital age zero. Firms which are close from the technology frontier own relatively new capital. On the other hand, firms which are far from the technology frontier own capital with high age. Our model predicts a positive capital age risk premium. In this section, we perform asset pricing tests using model–generated data to quantitatively explore this positive relation between capital age and equity returns in the cross section.

3.3.1 Capital Age sorted portfolios

In the model, we measure the capital age of a firm as the number of quarters since the firm's last adoption decision. Once a firm adopts the technology frontier, we reset its capital age to zero by assuming that it reinstalls all of its capital using the latest technology.

We use artificial data to create ten portfolios sorted on capital age that we rebalance at a quarterly frequency. Table 3 reports the average portfolio returns and the asset pricing test results. Panel A show that the average return of old capital firms (column 'O') is higher than the average return of young capital firms (column 'Y'). The implied return differential (column 'OMY') is about 6% per annum for value weighted portfolios.

We then test the standard capital asset pricing model (CAPM) using the ten value-weighted portfolios sorted on capital age as test assets. The market return is defined as the average return across all stocks weighted by their market equity. The market factor (Mkt_{t+1}) is the difference between the market return and the risk-free rate. We test the CAPM using the time-series regression,

$$R^e_{j,t+1} = \alpha_j + \beta_{j,M}\text{Mkt}_{t+1} + \epsilon_{j,t+1}, \tag{14}$$

where $R^e_{j,t+1}$ denotes the portfolio excess return, $\beta_{j,M}$ measures the quantity of the market risk, and α_j denotes the abnormal return. The results reported in Table 3 show that the market risk does not explain the cross sectional risk premium. In the model, all the portfolios share the same quantity of market risk ($\beta_{j,M} = 1$). The market beta of the OMY portfolio is almost zero. Consistently, the annual abnormal return of the value-weighted OMY portfolio is about 6%. The CAPM fails in explaining these portfolios sorted on capital age.

Then we investigate a two factor model where the market excess return is the first factor and the technology frontier shock the second. We decompose the capital age portfolio excess returns into the price of risk and quantity of risk using this two factor model. Specifically, we estimate the quantity of risks using the following time-series regression,

$$R^e_{j,t+1} = \alpha_j + \beta_{j,M}\text{Mkt}_{t+1} + \beta_{j,N}\sigma_N\eta_{j,t+1} + \epsilon_{j,t+1}, \tag{15}$$

where $R^e_{j,t+1}$ denotes the portfolio excess return, $\beta_{j,M}$ is the market beta, $\beta_{j,N}$ measures the quantity of risk for the technology frontier shock ($\sigma_N \eta_{j,t+1}$). The Panel A in Table 3 reports the estimation results. Through this decomposition, we find that firms with old capital are more exposed to the technology frontier shock than firms with young capital. With the assumption of a positive price for the technology risk, the exposures on the technology frontier shock across the capital age portfolio explain the cross sectional expected returns. Notably, the market betas remain flat across all the portfolios as in the CAPM tests. In contrast, the betas of the technology frontier shock ($\sigma_N \eta_{j,t+1}$) varies substantially across the age portfolios. In particular, old capital firms load more on the technology frontier shock (TFS) than young capital firms. The beta of the spread OMY portfolio is 0.41 for the value weighted portfolio (not tabulated). Even though old and young capital age firms have the same exposure to market risk, they differ in their exposure to the technology frontier risk. This is the channel that generates the cross–sectional variations in returns across the capital age-sorted portfolios.

3.3.2 Value premium

In this section, we explore the cross sectional risk premia of the book-to-market portfolios predicted by the model. Specifically, we form ten value-weighted and ten equal-weighted portfolios sorted on firms' book-to-market ratios (BM). We define the book-to-market ratio as the ratio of physical capital over ex-dividend stock value. The portfolios are rebalanced at quarterly frequency and the reported returns are annualized. Panel B in Table 3 reports the average excess returns, t-statistics and the Sharpe ratios of these portfolios.

The model generates a sizable value premium of 3.1% per year. This happens because value firms in the model have higher capital age and are more exposed to the technology frontier shocks than the growth firms which are low capital age firms. The lower part of Panel B reports the corresponding asset pricing test results. The model implied CAPM alpha for the value premium is 2.8% per annum and is statistically significant, whereas the market beta is insignificant. Therefore, the unconditional CAPM fails to capture the value premium in the model, consistent with the empirical fact documented in the literature.

3.4 Inspecting the mechanism

In this section we perform several analyses to understand the economic mechanism driving the cross sectional returns in the model. We several alternative specifications of the model and compare the key moments with the benchmark model. Table 4 reports the results.

The role of a positive λ_η*:* We first set the price of the technology frontier shock (λ_η) to be zero. In this specification, even though the technology frontier shock affects firms' cash flows, it does not affect the marginal utility of investors and thus it is not a priced risk. Stock returns load on this shock. However, the risk exposure to this shock is not associated with any risk premium. This can be observed from Specification 2 in Table 4. The beta to the technology frontier shock (TF-shock) after controlling for the market factor for old capital stocks is 0.19. In contrast, the beta to the technology frontier shock for young capital stocks is -0.29. The old-minus-young spread portfolio's beta to the technology frontier is 0.48, a value almost identical to the one in the benchmark case.[4] However, because $\lambda_\eta = 0$, the capital age spread drops to almost 0. It is also interesting to note that not only the capital age spread drops to 0, all other cross sectional risk premia reduce to almost 0 as well. This is not surprising because the technology frontier shock is the only shock to which stocks have heterogeneous exposure in the model. Therefore, we find that a positive λ_η is necessary for the model to generate cross sectional risk premia.

The role of adoption costs. The presence of fixed technology adoption cost is key to match both firms' investment dynamics and cross sectional risk premia. In Specification 3, we set $f_i = 0$, i.e., there is no fixed investment cost. In this case, the average capital age drops from 20 quarters in the benchmark case to 3 quarters. This is because all firms are more willing to adopt the latest capital vintage, thus generating a lower average capital age in the economy. Without fixed adoption costs, firms burdened with old capital can now upgrade to the frontier technology making them less risky than the benchmark calibration, which causes a sharp reduction in the cross sectional risk dispersion; the capital age spread is almost 0%. Note that the implied value premium also becomes negative when the technology adoption is cost free. This is quite

[4]The choice of the price of risk can also affect stock's risk exposure (betas) through the channel of driving the optimal investment rate and hence stock valuation.

intuitive: Value firms now use the free technology to smooth their dividend streams thus are not exposed to the technology frontier shocks.

The role of operating costs. The removal of the fixed operating cost does not affect the optimal adoption policy, thus the mean capital age remains the same as in the benchmark economy. However, the magnitude of the fixed operating cost has a large impact on the model's ability to generate a value premium, because it affects cash flows through the operating leverage channel. In the specification 4 without a fixed operating cost, the implied value premium becomes negative at -0.3%.

The role of technology risk. In the last specification, we explore the role of technology risk for asset returns. We make this risk negligible (i.e., $\sigma_N = 0$) and keep the price of risk the same as the benchmark model, we find that there is virtually no heterogeneity in cross-sectional equity returns.

In summary, we find that a positively priced sizable technology frontier shock and a fixed adoption cost are important for the model to generate sizable cross sectional variations of stock returns in the model.

4 Estimation of capital age

As discussed in the related literature, the firm's capital age is not directly observable. Because there is no readily available data on capital age, we follow the methodology in the industrial organization literature to estimate firms' capital age of the U.S. public companies. The estimation of capital age is important for our analysis, because it allows us to test the models' economic predictions in the data.

4.1 Data

Monthly stock returns are from the Center for Research in Security Prices (CRSP), and accounting information is from the CRSP/Compustat Merged Quarterly Industrial Files. The sample is from quarter 3 of 1976 to quarter 4 of 2016 and includes firms with common shares (shrcd=10 and 11) and firms traded on NYSE, AMEX, and NASDAQ (exchcd=$1, 2$, and 3). We omit firms whose primary standard industry classification (SIC) is between 4900 and 4999 (utility/regulated firms) or between 6000 and 6999 (financial firms). We also exclude R&D–intensive sectors (SIC codes 737, 384, 382, 367, 366, 357, and 283) from our sample,[5] because our theoretic model applies to the firms that upgrade the technology through investing in the latest machines and equipment, which is not necessarily suitable to study the R&D-intensive firms whose investments are primarily in knowledge development, know-how, and wages/salaries for scientists and engineers (e.g., Brown and Petersen (2011)). In total, our sample consists of 288,085 firm–quarter observations. All the quantities are winsorized at the top and bottom 1 percentiles to attenuate the impact of outliers.

4.2 Estimation of capital age in the data

We measure capital age following the methodology in Salvanes and Tveteras (2004). We start by defining an initial measure of firm–level capital stock ($K_{i,0}$) for firm i using net property plant and equipment (Compustat item *ppentq*) and an initial measure of firm–level capital age. The latter quantity is calculated using the ratio of accumulated depreciation and amortization (item *dpactq*) over current depreciation and amortization (item *dpq*)[6]. Then we recursively build a measure of firm–level capital stock using

$$K_{i,t+1} = K_{i,t} + I^N_{i,t}, \tag{16}$$

where $I^N_{i,t}$ is net investment of firm i between period t and $t+1$. Net investment is defined as the difference in net property plant and equipment (item *ppentq*) between two consecutive quarters. We define gross investment as $I_{i,t} = \delta_j K_{i,t} + I^N_{i,t}$, where δ_j is the depreciation rate of

[5]We define R&D–intensive sectors following the definition of Brown, Fazzari, and Petersen (2009).

[6]Calculating an asset's average age using accumulated depreciation over current depreciation is standard practice in financial accounting (e.g., Rich et al. (2014) among many others). If accumulated depreciation and amortization in a given fiscal quarter is missing, we use the end of the fiscal year values. In the few instances where the fiscal year end–value is missing, we use the following estimated value: $\widehat{dpactq} = \hat{\beta}_j K_t$, where $\hat{\beta}_j$ is the pooled OLS estimate in the 2–digit SIC industry j. These estimated values represent 2% of the initial capital age measure and their exclusion has no material impact on the analysis. As an initial value of capital age, we also use an average industry historical-cost average age from the BEA discarding the first 4 quarters and obtain very similar results.

industry j calculated using depreciation data from the BEA. All the quantities are expressed in 2009 constant dollars using the seasonally adjusted implicit price deflator for non–residential fixed investment.

Once we have a time–series of capital stock and gross investment observations at the firm level, we follow Salvanes and Tveteras (2004) and define the capital age of firm i at time t as:

$$AGE_{i,t} = \frac{(1-\delta_j)^t K_{i,0}(AGE_{i,0}+t) + \sum_{j=0}^{t-1}(1-\delta_j)^{t-j-1} I_{i,j}(t-j)}{K_{i,t}}. \tag{17}$$

In the above formulation, capital age at each time t is a weighted average of the age of each capital vintage. The weights are the relative importance of each capital vintage in determining total capital in place at time t. We assume that a firm always installs the newest capital when it invests so that if a firm has capital age equal to $AGE_{i,0}$ at time $t = 0$, then the time $t = 1$ capital age is a weighted average of the new installed capital vintage, which has age 1, and the old vintage which after one period has age $AGE_{i,0} + 1$. The weights are $(1 - \delta_j)K_{i,0}/K_{i,1}$ for the past vintage and $I_{i,0}/K_{i,1}$ for the new vintage, where $K_{i,1} = (1 - \delta_j)K_{i,0} + I_{i,0}$.

For analytical convenience, we assume that when a firms disinvests it disposes of all capital vintages in proportion to their contribution to the total installed capital. Under this assumption, the formulation in Equation (2) can be rewritten recursively as

$$AGE_{i,t} = (1-\delta_j)\frac{K_{i,t-1}}{K_{i,t}}(AGE_{i,t-1}+1) + \frac{I_{i,t-1}}{K_{i,t}}, \tag{18}$$

so that $AGE_{i,t} = AGE_{i,t-1} + 1$ when the firm has no positive investment. In addition, the above formulation implies that a firm can reduce the capital age only via positive investment, as in our model economy.

4.3 Summary statistics

In addition to capital age, we also keep track of the following variables, the (gross) investment rate, return on equity (ROE), market capitalization (i.e., size), and the book–to–market ratio. Their detailed definition is in Appendix A3.

Panel A in Table 5 reports the summary statistics for the measure of capital age and the above variables. The mean (median) firm-level capital age in the sample is 22 (20) quarters with a volatility of 11 quarters, implying that firms on average upgrade the obsolete capital every 5.5 years. Quarterly firm-level investment rate is 5.2% with a volatility of 14.2%. The average firms' return on equity and book-to-market ratio are 0.3% and 0.82, respectively, with respective volatilities of 11.4% and 0.67, consistent with the range of empirical estimates in the literature. The average size of the firms in the sample is $1,499$ million in 2009 dollar term.

A natural concern for the measure of capital age is whether the capital age merely captures the (inverse) investment effect (firms with new capital invest more). Panel B in Table 5 reports the correlation matrix of the variables used in the empirical analysis. Notably, capital age and investment rate are only moderately correlated at -0.25, suggesting that capital age and investment contain different information. Capital age is also only weakly correlated with book-to-market with the correlation of 0.17. Lastly, capital age is mildly correlated with return on equity and size with the respective correlations of 0.11 and 0.12.

4.4 Alternative measure of capital age

We also consider an alternative (albeit related) measure of capital age to show the robustness of our main measure of capital age. Specifically, we calculate capital age under the assumption that when $I_i \leq 0$ the firm disposes of oldest capital vintages first. We do this because we do not observe the sales of capital disaggregated at the vintage level and because it is plausible to assume that disinvestment activities concern less productive (i.e., oldest) capital (Salvanes and Tveteras (2004)). The drawback of this alternative approach is that we lose the convenient recursive formulation in Equation 18.

Overall, the alternative measure of capital age delivers similar summary statistics to our baseline measure of capital age and it also produces similar correlations with the key variables used in the empirical analysis. Table 5 reports the results. For example, the alternative measure of capital age has a mean of 19 quarters with a volatility of 10 quarters, fairly close to those of the baseline measure of capital age. More importantly, the correlation between the alternative measure of capital age and our baseline measure is quite high, at 93%, suggesting that these measures of capital age capture the same information about firms' investment in capital. The alternative measure of capital age is weakly correlated with investment, return on equity and book-to-market with correlations of −0.21, 0.14, and 0.16, respectively. We report the results from several robustness checks using the alternative measure of capital age in Appendix A4.

5 Empirical analyses

In this section, we provide evidence on the relation between capital age and the cross–section of equity returns. We first show that capital age positively predicts the cross sectional expected stock returns, consistent with the model. Then we perform a battery of asset pricing tests. Lastly, we investigate the joint link between capital age and other firm-level characteristics on one hand and future stock returns in the cross section on the other using multivariate regression techniques.

5.1 Capital age spread

To investigate the link between capital age and future stock returns in the cross section, we construct ten portfolios sorted on the firm's current capital age and report the portfolio's post-formation average stock returns. We construct the capital age portfolios at a quarterly frequency as follows. At the beginning of January, April, July, and October of each year, we sort the universe of common stocks into ten portfolios based on the firm's capital age 6 months prior to portfolio formation. We define the capital age breakpoints used to allocate firms into portfolios by using all firms in NYSE-AMEX-NASDAQ. Once the portfolios are formed, their returns are tracked from January/April/July/October of year t to March/June/September/December of year t. The procedure is repeated at the year $t + 1$.

We report both average equal- and value-weighted portfolio returns across all firms. Reporting these two sets of average returns allows us to provide a comprehensive picture of the link between capital age and stock returns in the overall economy. The top rows in Panel A of Table 6 report the average excess stock returns (r^e, in excess of the risk-free rate) and Sharpe ratios of the ten capital age sorted portfolios. This table shows that, consistent with the model, across the two sets of average returns, the firm's capital age forecast stock returns. Firms with currently low capital age earn subsequently lower returns on average than firms with currently high capital age. The difference in returns is economically large and statistically significant.

The average equal-weighted return spread (O-Y, the capital age return spread) is 15.3% per annum, and this value is more than 5.6 standard errors from zero. The average value-weighted capital age return spread is 9.2% per annum, and this value is more than 2.4 standard errors from zero. From the fact that the capital age return spread is smaller in value-weighted returns than in equal-weighted returns, we can infer that the capital age return spread is particularly strong among small firms, a common finding in the empirical asset pricing literature.

The Sharpe ratios of the capital age portfolios are also increasing in firms' current capital age. Across the two sets of average returns, the Sharpe ratio of the portfolio of firms with high capital age is more than ten times larger than the Sharpe ratio of the portfolio of firms with low capital age.

5.2 Capital age, investment, book-to-market, size and returns

Previous studies document a negative relationship between the firm's investment rate and future stock returns in the cross section. As reported in Table 5, the capital age and investment rates are negatively correlated. Thus, part of the link between the firm's capital age and future stock returns may reflect the negative correlation between investment and future stock returns. In this section, we extend the previous analysis to investigate the joint link between capital age, investment, and future stock returns in the cross section.

To this end, we form nine portfolios two-way-sorted on capital age and investment as follows. At the beginning of January, April, July, and October of each year t, we unconditionally sort the universe of common stocks into three portfolios based on the firm's investment rate and into three portfolios based on the firm's capital. The investment rate and capital age breakpoints for year t are the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of the corresponding sorting variable at the end of each quarter 6 months prior to portfolio formation. To compute the breakpoints, we use the sample of all firms in NYSE-AMEX-NASDAQ, consistent with the construction of the portfolios one-way-sorted on capital age. Once the portfolios are formed, their returns are tracked from January/April/July/October of year t to March/June/September/December of year t. The procedure is repeated at the year $t+1$.

Panel A in Table 7 shows that the two-way sorting procedure generates a reasonable spread in average excess returns across both the capital age (column O-Y) and the investment rate (row H-L) dimensions. Within investment bins (within rows), firms with low capital age earn lower returns on average than firms with high capital age. Within capital age bins (within columns), firms with low investment rates earn higher returns on average than firms with high investment rates. Thus, the capital age contains some information about future stock returns that is not contained in the investment rate (and vice versa for the investment rate).

The magnitude of the capital age spread tends to be higher than the magnitude of the investment return spread. In addition, the investment and, especially, the capital age spreads are stronger in equal-weighted returns than in value-weighted returns. In equal-weighted returns (across all firms), within each investment bin, firms with high capital age outperform firms with low capital age by a value between 9% to 14% per annum and the spreads are all significantly different from zero. Similarly, within each capital age bin, firms with low investment rate outperform firms with high investment rate by a value between 2% to 7% per annum and also in this case the spreads are all significantly different from zero. Taken together, the results show the coexistence of a capital age and investment return spread in the data, and this coexistence is stronger in equal-weighted average returns.

Furthermore, we also form two sets nine portfolios two-way-sorted on capital age and size and capital age and book-to-market, respectively. To briefly summarize the main findings, Panel B of Table 7 shows that the capital age spread remains positive and significant in every size bin in both equal-weighted and value-weighted portfolios, with the only exception of value-weighted large size portfolios. In addition, the age spread decreases across size categories when returns are value weighted and it is larger for medium size firms when returns are equally weighted.

Turning to the two-way-sorted portfolios on capital age and book-to-market (Panel C of Table 7), in equally-weighted returns the age spread remains positive and significant in each book-to-market bin; in value-weighted returns, the age spread is significant for medium and high book–to–market bins.

5.3 Asset pricing tests

We also investigate the extent to which the variation in the average returns of the capital age portfolios can be explained by exposure to standard risk factors, as captured by the unconditional capital asset pricing model (CAPM), or the Fama-French (2015) five-factor model (FF5), or the Hou-Xue-Zhang (2015) four-factor model (HXZ). This analysis is important because it provides information about the class of models that can potentially explain the capital age spread.

To test the CAPM, we run monthly time-series regressions of the excess returns of each portfolio on a constant and the excess returns of the market portfolio (market). To test the Fama-French five-factor model, we augment the previous CAPM regressions with the size factor (SMB, small minus big), the value factor (HML, high minus low), the profitability factor (RMW , robust minus weak) and the investment factor (CMA, conservative minus aggressive). For the Hou-Xue-Zhang four-factor model, we augment the previous CAPM regressions with their size factor (ME), investment factor (IA) and profitability factor (ROE). The intercepts from these regressions are the pricing errors (abnormal returns).

Panels B to D of Table 6 report the intercepts for the CAPM, the Fama-French five-factor model and the Hou-Xue-Zhang four-factor regressions on the ten capital age portfolios. Clearly, the CAPM cannot explain the pattern of average returns of these portfolios. The CAPM-implied pricing errors are large, with a mean absolute pricing error of 4.8% per annum using equal-weighted returns and 3.1% per annum in value-weighted returns. The pricing error of the capital age spread portfolio is large and significant, between 18.2% per annum for equal-weighted returns and 14.5% for value-weighted returns.

The previous analysis shows that the CAPM-implied pricing error of the capital age spread portfolio is larger than the capital age return spread itself. As such, the large CAPM pricing errors represent a higher hurdle for theoretical models than the capital age spread itself. This result follows from the fact that the market betas (b) of the portfolios, the relevant measure of the quantity of risk of each portfolio according to the CAPM, goes in the wrong direction across the capital age portfolios. The portfolio of firms with currently high capital age has a lower market beta than the portfolio of firms with currently low capital age, which is inconsistent with the higher average returns (risk) of the high capital age portfolio.

The Fama-French five-factor model and the Hou-Xue-Zhang model do a better job here than the CAPM for both equal- and value-weighted returns. The mean absolute pricing errors of the Fama-French model drops significantly relative to the mean absolute pricing errors of the CAPM (2.1% here versus 4.8% in the CAPM in equal-weighted returns, 2.4% here versus 3.1% in the CAPM in value-weighted returns,). However, the Fama-French model still fails to capture the returns of the capital age spread portfolio of both equal- and value-weighted returns. The abnormal return of the capital age return spread portfolio is 10.0% and 5.3% per annum, respectively in equal- and value-weighted returns, and these values are 5.5 and 2.4 standard errors from zero. The mean absolute pricing errors of the Hou-Xue-Zhang model also drops significantly relative to the mean absolute pricing errors of the CAPM (2.3% here versus 4.8% in the CAPM in equal-weighted returns, 1.8% here versus 3.1% in the CAPM in value-weighted returns). The abnormal return of the capital age return spread portfolio implied by the Hou-Xue-Zhang model is 8.1% and 5.0% per annum, respectively in equal- and value-weighted returns, and these values are 5.5 and 2.4 standard errors from zero. In untabulated results, we also include the liquidity factor of Pastor and Stambaugh (2003) on top of FF5 and HXZ to control for liquidity–related issues and the results are virtually unchanged[7].

The asset pricing tests for the nine portfolios two-way-sorted on capital age on one hand and investment rate, market equity, and book-to-market ratio on the other are reported in Table 8. For the capital age and investment rate sorted portfolios, the risk–adjusted alphas across the three linear factor models are always positive and significant for the equally weighted portfolios, except for the low investment rate category when we use the HXZ factors. The results are weaker when we use value-weighted portfolios. The risk-adjusted capital age spread is positive and significant only when we use the CAPM. The reason being that both FF5 and HXZ have an investment–based factor that seems to pick up variability in capital age sorted portfolios only when we double sort using the investment rate.

The results in Table 8 also show that the capital age spread remains positive across all the size and book-to-market categories (with the only exception of the large size category when we use FF5 and HXZ) and it is significantly different from zero at the 5% level in most of the cases (28 out of 36).

Taken together, the Fama-French five-factor model and the Hou-Xue-Zhang model capture a

[7] The Fama and French factros are from Kenneth French's website (*http : //mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*), while the liquidity factor is from Lubos Pastor's website (*http : //faculty.chicagobooth.edu/lubos.pastor/research/*). We thank Lu Zhang for kindly providing the Hou, Xue, and Zhang factors.

larger fraction of the cross-sectional variation in the average returns of the capital age portfolios than the CAPM, but these two factors model cannot explain the capital age spread when we use single sorts or double sorts on size and book–to–market. Not surprisingly, the capital age spread is only subsumed when we control for the investment rate, which is one of its key determinants. In the next section, we go beyond two-way-sorted portfolios and control for multiple characteristics simultaneously by running cross–sectional regressions.

5.4 Firm-level return predictability regressions

In this section, we extend the previous analysis to investigate the joint link between capital age, investment, size, book-to-market and future stock returns in the cross section using firm-level multivariate regressions that include the firm's capital age and other controls as return predictors.

We also investigate the marginal (relative to investment and other predictors) predictability of capital age using stock return predictability regressions performed at the firm-level. It is difficult to draw inferences about which sorting variables have unique information about future returns using a portfolio approach. The portfolio procedure requires the specification of breakpoints to sort the firms into portfolios and the selection of the number of portfolios. These choices may influence the overall analysis. Thus, the firm-level regressions provide a cross-check.

We run standard firm-level cross-sectional regressions (Fama and MacBeth, 1973) as well as pooled time series ordinary least squares (OLS) regressions to predict stock returns using the lagged firms' capital age, investment rates (IK), size, book-to-market (BM) and profitability (ROE) as return predictors. The time series regression allows for a clear economic interpretation of the regression slopes, and the two different econometric procedures allows us to further validate the results. We also include the previous month return in all regressions to control for persistence in equity returns. All the control variables are divided by their unconditional standard deviation to facilitate the comparison across regressions.

Panel A in Table 9 reports the results from cross-sectional predictability regressions performed at a monthly frequency. The reported coefficient is the average slope from monthly regressions and the corresponding t-statistic is the average slope divided by its time-series standard error. The reported R^2 is the time–series average of the cross–sectional R^2. The results are consistent with the portfolio-level results. In specification 1, capital age significantly predicts future returns with a slope coefficient of 0.41, which is more than 6 standard errors from zero. It implies that that a one standard deviation increase in (log) capital age leads to a significant increase of 0.41% in the average monthly equity return. The difference in average (log) capital age between firms in the top and bottom decile is equivalent to 2.15 standard deviations. The coefficient in Column 1 implies a difference in expected returns of 0.90% per month, which is equivalent to an annualized difference of 10%, a value close to 9%, the value–weighted age premium reported in Table 6.

In specifications 2 to 5, capital age predicts stock returns with statistically significant positive slope coefficient after controlling for investment, size, book-to-market and ROE one by one. The estimated capital age slope coefficient ranges from 0.43 (specification 2) to 0.32 (in specification 3, controlling for the effect of book-to-market), and these values are all more than 5 standard errors from zero. It's worth noting that in specification 6, the slope of capital age remains positive and significant after we include all the regressors, albeit its magnitude is 30% smaller than the value in specification 1. In this case, a one standard deviation increase in capital age leads to a significant increase of 0.28% in the average monthly equity return, which translates in an annualized return of 3.4%.

Panel B of Table 9 reports the results from pooled OLS predictability regressions. The estimation here is performed at a quarterly frequency, and includes firm and quarter fixed effects.[8] The capital age slope coefficients are positive and significant in all specifications. Interestingly, in specifications 2 and 4, size and investment rates become insignificant with the capital age as a predictor in the regressions.

5.5 The capital age spread and technology adoption shocks

In the previous sections, we show that the capital age spread is a priced characteristic in the cross-section of equity returns. In this section, we provide evidence on the link between the capital age spread and an aggregate measure of technology adoption shock. To this end, we follow Baron and Schmidt (2017) and use aggregate data on the introduction of technology

[8]Clustering standard errors at the time and firm level produces very similar results.

standards over the period 1976q3–2011q4 to capture the adoption of new technologies.[9]

The key macroeconomic variable that we use is the number of technology standards released each quarter by both US and international standard setting organizations (SSOs) in two main groups closely related to technology adoption: Telecommunication, Audio and Video Engineering (International classification of standards (ICS) class 33) and Information Technology and Office Machines (ICS class 35). The technology adoption shock is the log difference (i.e., the growth rate) in the number of new technology standards.[10]

To test if the technology adoption shock is a source of systematic risk, we consider a two-factor asset pricing model with the stock market factor (MKT) and the technology adoption shock ($TECH$) as the two factors. Specifically, we use the following stochastic discount factor (investors' marginal utility):

$$M_t = 1 - b_M \times \mathrm{MKT}_t - b_{Tech} \times \mathrm{Tech}_t, \tag{19}$$

which states that investors' marginal utility is driven by two aggregate shocks, MKT, which is the market factor in the standard capital asset pricing model (CAPM), and the technology adoption shock. Note that the specification of the stochastic discount factor in Equation (19) is closely related to that in the model given in Equation (10) because the market factor is used here as a proxy for the aggregate productivity shock. We then estimate the risk factor loadings on the two aggregate shocks (b_M and b_{Tech}) by the generalized method of moments (GMM) using the standard asset pricing moment condition $E\left[r_{it}^e M_t\right] = 0$, in which r_{it}^e is the excess return on test asset i. To help in the interpretation of the results, this moment condition can be written as:

$$E\left[r_{it}^e\right] = \alpha_i + b_M \mathrm{Cov}(\mathrm{MKT}_t, r_{it}^e) + b_{Tech} \mathrm{Cov}(\mathrm{Tech}_t, r_{it}^e), \tag{20}$$

where we added the term α_i (alpha), the pricing error (abnormal return) associated with asset

[9] We are very grateful to Justus Baron and Julia Schmidt for sharing their data on technology standards. More information can be found at http://www.law.northwestern.edu/research-faculty/searlecenter/innovationeconomics/data/technologystandards/

[10] We obtain stronger results if we follow Baron and Schmidt (2017) and use a citation-weighted measure that gives more importance to technology standards more widely adopted. However, the citation-weighted measure uses references for a technology standard over the subsequent 4 years. To avoid a potential look–ahead bias in our results, we use the raw count of standard releases by US and International SSOs.

i.

In addition to the technology adoption shock, we also test the pricing properties of following macroeconomic variables related to systematic risk: the log change in real GDP, the log change in utilization adjusted total factor productivity (TFP), the log consumption-wealth ratio (cay), the Pastor and Stambaugh (2003) aggregate liquidity shock, the log change in the BAA-AAA spread, and the change in macroecomonic uncertainty. All the data are at a quarterly frequency over the period 1976:3–2014:4.[11].

We first look at the pricing properties across the 10 value-weighted capital age-sorted portfolios. In Panel A of Table 10 we report the pricing error across the 10 portfolios and for the old minus young portfolios (OMY). These pricing errors are generated by a two-factor model with the market excess return and one macroeconomic shock at the time. We also report the slope (i.e., the *beta*) for the macroeconomic shock of a regression of each portfolio excess return over market excess return and the macroeconomic shock. A result stands out: the technology adoption shock is the only shock that produces non significant pricing errors across all portfolios and a significant difference in betas (i.e., different risk exposure) between the old and young portfolios. The other macroeconomic shocks either fail in generating a significantly different risk exposure or a non significant excess return between the old and young portfolios.

In Panel B, we report the results of the one-step GMM estimation of the SDF in Equation 19. To facilitate comparison, the all factors are demeaned and divided by their unconditional standard deviation. The one factor model that uses only the market excess retuns produces an mean absolute error (m.a.e.) of 0.89. Adding the technology adotpion shock as a second factor decreases the m.a.e. to 0.30. The improvement in m.a.e. generated by the other macroeconomic shocks is not as dramatic: the m.a.e. goes from 0.58 to 0.82. We also estimate a three factor model with the market excess return, the technology adotpion shock, and one

[11]The data for real GDP and for the BAA and AAA corporate bond yields are from the Federal Reserve Economic Databease (FRED) at the Federal Reserve Bank of St. Louis (`https://fred.stlouisfed.org`). The data on utilization adjusted total factor productivity (TFP) are from the Federal Reserve Bank of San Francisco (`http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/`). The data on the consumption-wealth ratio and macroeconomic uncertainty are from Sydney Ludvigson's website (`https://www.sydneyludvigson.com/data-and-appendixes/`). Macroeconomc uncertainty is the 1-month ahead measure computed as in Jurado, Ludvigson, and Ng (2013). The aggregate liquidity shock is from Lubos Pastor's website (`http://faculty.chicagobooth.edu/lubos.pastor/research/`). The aggregate liquidity shock is available at a monthly frequency, we use a quarterly version by summing up the shocks in each given quarter.

other macroeconomic factor. Panel B shows that the risk factor loading on the technology shock remains always significant and its estimated value does not change dramatically across the different specifications. It is worth noting that none of the other macroeconomic factor is significant when we also include the technology adotpion shock.

Panel A and Panel B validate our model's prediction that capital age is a source of risk at the firm level becasue it entails a different exposure to a technology adoption shock. In Panel C of Table 10, we explore if this source of risk is also priced in a different set of test assets. To this end. we follow Gospodinov, Kan, and Robotti (2014) and consider the quarterly excess returns on the 6 size and book-to-market Fama-French portfolios, the 17 Fama-French industry portfolios, and the 10 momentum portfolios. As in Panel B, we test both a two-factor and a three-factor model. The results are consistent with the ones in Panel B. The risk factor loading on the technology shock is significant in the two-factor model and always significant in the various three-factor model specifications with the only exception of the model that includes the TFP shock. Note that *cay*, the liquidity shock, the credit shock, and the uncertainty shock have all a significant risk factor loading in the two-factor model that becomes not significant when we include the technology adoption shock.

Overall, the data points toward technology adoption shocks as a source of systematic risk that is priced in the economy.

6 Conclusion

We study the impact of the variation of the aggregate technological frontier on firms' asset prices in a dynamic model economy. Our results show that costly technology adoption combined with a systematic technology frontier shock are important in determining the cross section of stock returns. In our setting, technology adopting firms are less risky than non-adopting firms because non-adopting firms are more likely to adopt the technology frontier in the near future with positive productivity shocks. In the model, old capital age firms and value firms are non-adopting firms, thus, the model generates sizable capital age and value spreads. We provide empirical evidence for the model predictions. In particular, we find an annual return spread of 9% between old and young capital firms. The standard asset pricing factor models fail fails in explaining this return spread.

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A1 Detrending the model

Because both aggregate productivity and the technology frontier follow random walk processes and hence non-stationary, we need to detrend the model before we can apply the value function iteration method to solve the model. Define detrended variables

$$
\begin{aligned}
v_t &= \frac{V_t}{X_t N_t} && (21) \\
k_t &= \frac{K_t}{N_t} && (22) \\
d_t &= \frac{D_t}{X_t N_t}. && (23)
\end{aligned}
$$

After some algebra, the firm problem is equivalent to

$$
v_t = \max_{\phi_t} d_t + e^{G-\frac{1}{2}\lambda_\eta^2+g_N+\sigma_N\eta_t}\mathrm{E}_t\left[e^{-\lambda_\eta\eta_{t+1}}v_{t+1}\right], \tag{24}
$$

where

$$
\begin{aligned}
d_t &= e^{z_t}k_t - \left[f_i k_t + i_t k_t\right]\phi_t - f_o && (25) \\
G &= -r + g_x + \frac{1}{2}\sigma_x^2 - \sigma_x\lambda_e. && (26)
\end{aligned}
$$

ϕ_t is an indicator function which equals 1 if the firm adopts the technology frontier ($\phi_t = 1$) and 0 otherwise.

The detrended k_t follows

$$
k_{t+1} = \begin{cases} (1-\delta)k_t e^{-g_N-\sigma_N\eta_t} & \text{if} \quad \phi_t = 0 \\ 1 & \text{if} \quad \phi_t = 1 \end{cases} \tag{27}
$$

After detrending, the firm's investment rate is given by

$$i_t = \begin{cases} 0 & \text{if} \quad \phi_t = 0 \\ \frac{1}{k_t} e^{g_N + \sigma_N \eta_t} - 1 + \delta & \text{if} \quad \phi_t = 1 \end{cases} \tag{28}$$

After detrending, there are three state variables in this economy (z_t, η_t, k_t). The firm value and policy functions such as optimal investment rate are functions of these three state variables.

A2 Numerical algorithm

We use the value function iteration procedure to solve the detrended firm's maximization problem as in Section A1. The value function and the optimal adoption decisions ($\phi_t = 0$ or 1) are solved on a grid in a discrete state space. We specify one grid of $3,000$ points for the detrended capital (k_t). The grid is equally spaced for log k_t. In particular, we include $k_t = 1$, which represents the detrended capital adopting to the technology frontier, as one of the grid points to reduce interpolation errors for this important state.

The technology frontier shock η_t is an i.i.d. standard normal shock. We discretize η_t into 9 grid points using Gauss-Hermite quadrature. The firm-specific productivity (z_t) has continuous support in the theoretical model, but it has to be transformed into discrete state space for the numerical implementation. Because the firm-specific productivity process z_t is highly persistent, we use the method described in Rouwenhorst (1995) for a quadrature of the Gaussian shocks. We use 7 grid points for the z_t. 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. The Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation is used to obtain the continuation value of a firm that does not lie directly on the grid points. Finally, we use a simple discrete global search routine in maximizing the firm's problem.

A3 Data definitions

We measure the investment rate as gross investment ($\delta_j K_{i,t} + I^N_{i,t}$) divided by the beginning of the period capital stock ($K_{i,t}$). Profitability is income before extraordinary items (item *ibq*) divided by the previous quarter book value of equity. The latter quantity is constructed following Hou, Xue, and Zhang (2015) and it is equal to shareholders' equity (item *seqq*) plus deferred taxes and investment tax credit (item *txditcq*, if available) minus the book value of preferred stock (item *pstkrq*). If shareholders' equity is not available, we use common equity (item *ceqq*) plus the carrying value of the preferred stock (item *pstkq*). If common equity is not available, we measure shareholders' equity as the difference between total assets (item *atq*) and total liabilities (item *ltq*). The book–to–market ratio is the book value of equity divided by the market capitalization (item *prccq* times item *cshoq*) at the end of the fiscal quarter. Market capitalization is calculated using data from CRSP and it is equal to the number of shares outstanding (item *shrout*) multiplied by the share price (item *prc*). When size is reported in levels, we express it in 2009 dollars using the personal consumption expenditure price deflator.

A4 Robustness Analyses

In this section we use the alternative measure of capital age to show that our results do not depend on the assumption on how the firm disposes of old capital vintages. Table A1 reports the value–weighted excess returns and CAPM alphas across the 10 capital age sorted portfolios, while Table A2 reports the value–weighted excess returns and alphas across the three factor models for the double sorted portfolios. Equal-weighted portfolios are omitted for economy of space, but available upon request. Overall, the results are consistent with the ones obtained using the recursive formulation for a firm's capital age.

Table 1: Parameter values under benchmark calibration

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

Parameter	Value	Description
Stochastic process		
$4g_N$	0.014	Average log growth of the technology frontier
σ_N	0.095	Volatility of log technology frontier
$4g_x$	0.012	Average log growth of aggregate productivity
σ_x	0.078	Volatility of log aggregate productivity
ρ_z	0.97^3	Persistence of firm-specific productivity
$\bar{z}$	-1.5	Long run average of firm-specific productivity
σ_z	0.21	Conditional volatility of firm-specific productivity
Technology		
δ	0.03	Rate of capital depreciation
f_i	3.4	Fixed cost of tehnology adoption
f_o	0.076	Fixed operating cost
Pricing kernel		
$4r$	0.022	The real risk-free rate
λ_e/σ_x	3	Risk price of aggregate productivity shock
λ_η/σ_N	4	Risk price of the technology frontier shock

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 reported statistics in the model are averages from 100 samples of simulated data, each with 5,000 firms and 30 years of monthly observations. Benchmark refers to the benchmark model. We report the cross-simulation averaged annual moments. The data moments are estimated from a sample from 1981 to 2014.

Moments	Data	Model
Asset prices		
Real risk-free rate	0.022	0.022
Market premium	0.057	0.065
Market Sharpe ratio	0.35	0.4
Average individual stock volatility	0.3	0.36
Value premium	0.067	0.033
Real quantities		
Std. dev. Of aggregate profits	0.14	0.17
Mean capital age (in quarters)	22	20
Std. dev. Of capital age (in quarters)	11	14
Cross sectional correlation (capital age and BM)	0.17	0.2
Cross sectional correlation (capital age and investment rate)	-0.25	-0.21

Table 3: Capital age and book-to-market sorted portfolios: returns and asset pricing tests

This table reports the excess returns and the asset pricing test results of ten value weighted portfolios sorted on capital age and ten value weighted portfolios sorted on book-to-market in the model. Panel A reports average excess returns and CAPM test results for capital age portfolios. Column'O' reports the portfolio consisting of firms with the oldest capital and Column 'Y' reports the portfolio consisting of firms with the youngest capital. Column 'OMY' reports the return difference of Portfolio 'O' and Portfolio 'Y'. Panel B reports average excess returns and CAPM test results for book-to-market portfolios. Column'G' reports the portfolio consisting of firms with the lowest book-to-market ratio (growth firms) and Column 'V' reports the portfolio consisting of firms with the highest book-to-market ratio (value firms). Column 'VMG' reports the return difference of Portfolio 'V' and Portfolio 'G'. The reported statistics in the model are averages from 100 samples of simulated data, each with 5,000 firms and 30 years of quarterly observations. Capital age in the model is the number of quarters for firms since the last technology adoption. The portfolio is rebalanced at quarterly frequency. All estimates of returns are annualized.

Panel A: Capital Age Portfolios

	Y	2	5	9	O	OMY
	Portfolio returns and Sharpe ratios					
$E[R^e]$	3.70	4.15	7.13	9.63	9.37	5.66
$[t]$	1.23	1.38	2.27	3.08	3.04	3.20
SR	0.22	0.25	0.42	0.55	0.54	0.55
	CAPM test: MAE = 1.97					
Alpha	-2.47	-2.15	0.28	3.14	2.86	5.33
$[t]$	-2.94	-2.87	0.30	2.58	2.28	3.20
MKT	0.97	0.98	1.03	0.99	0.97	0.00
$[t]$	35.67	39.22	55.74	25.21	24.53	-0.10
R2	0.91	0.93	0.96	0.83	0.83	0.01

Panel B: Book-to-Market Portfolios

	G	2	5	9	V	VMG
	Portfolio returns and Sharpe ratios					
$E[R^e]$	5.47	5.89	5.51	8.99	8.58	3.11
$[t]$	1.86	2.01	1.86	2.80	2.70	1.94
SR	0.34	0.36	0.33	0.51	0.49	0.41
	CAPM test: MAE = 1.05					
Alpha	-1.03	-0.67	-1.03	2.15	1.78	2.81
$[t]$	-1.65	-1.40	-1.49	2.11	1.77	1.86
MKT	0.98	0.99	0.99	1.03	1.03	0.04
$[t]$	56.51	71.12	48.37	34.74	40.15	0.96
R2	0.96	0.98	0.95	0.91	0.93	0.02

Table 4: Alternative model specifications

This table reports key moments generated by several alternative specifications. Model 1 is the benchmark economy. Model 2 sets the price of the technology frontier shock (λ_η) to zero. Model 3 sets $f_i = 0$, i.e., there is no fixed adoption cost. Model 4 sets $f_o = 0$, i.e., there is no fixed operating cost. Model 5 sets the volatility of the technology frontier (σ_N) to 0. The reported statistics in the model are averages from 100 samples of simulated data, each with 5,000 firms and 30 years of monthly observations. The portfolio is rebalanced at quarterly frequency. All estimates of returns are annualized.

Market	Market	Mean	E[R^e]			Beta to TFS			E[R^e]		
risk prem.	volatility	capital age	Y	O	OMY	Y	O	OMY	G	V	VMG
1. Benchmark											
6.50	16.12	19.73	3.70	9.37	5.66	-0.20	0.21	0.41	5.90	9.19	3.29
2. $\lambda_\eta = 0$											
7.42	19.93	23.75	7.49	7.35	-0.13	-0.29	0.19	0.48	7.35	7.48	0.13
3. $f_i = 0$											
14.29	19.86	3.20	14.28	14.28	0.01	0.00	0.00	0.00	14.43	13.98	-0.45
4. $f_o = 0$											
12.67	17.94	18.54	9.69	15.41	5.72	-0.21	0.19	0.40	11.64	11.34	-0.30
5. $\sigma_N = 0$											
7.29	15.94	20.22	7.27	7.25	-0.02	-0.48	0.10	0.58	7.26	7.32	0.06

Table 5: Summary Statistics

This table reports the mean, standard deviation, 25% percentile, 50% percentile, 75% percentile, and number of available observations for the variables used in the empirical analysis (Panel A) and their correlation (Panel B). We restrict our sample to companies listed in the three major stock exchanges (AMEX, NYSE, and NASDAQ). We exclude companies non incorporated in the USA, and we also exclude financials (SIC codes from 6000 up to 6999), utilities (SIC codes from 4900 up to 4999), and R&D–intensive sectors (SIC codes 737, 384, 382, 367, 366, 357, and 283) from our sample. The sample period is 1977q3–2016q4. All the data are winsorized at the top and bottom 1% to attenuate the impact of outliers. The 1%, 5%, and 10% significance levels are denoted with *** , ** , and * , respectively.

Panel A: Summary Statistics

	mean	sd	p25	p50	p75	obs
Capital Age	21.621	11.478	13.026	20.097	28.209	288,085
Capital Age Alt	19.549	10.134	11.986	18.074	25.253	272,123
Investment Rate	0.052	0.142	0.001	0.026	0.065	288,085
Return on Equity	0.003	0.114	-0.003	0.023	0.043	288,085
Size (2009 dollars)	1498.962	4368.24	36.612	164.773	799.278	288,085
Book-to-Market	0.817	0.669	0.372	0.632	1.043	288,085

Panel B: Correlation

	Capital Age	Capital Age Alt	Investment Rate	ROE	Size (2009 $)	Book Market
Capital Age	1					
Capital Age Alt	0.93***	1				
Investment Rate	-0.25***	-0.19***	1			
Return on Equity	0.11***	0.13***	0.05***	1		
Size (2009 dollars)	0.12***	0.12***	-0.02***	0.12***	1	
Book-to-Market	0.17***	0.15***	-0.14***	-0.03***	-0.17***	1

Table 6: Capital Age Sorted Portfolios and Tests of Standard Asset Pricing Factor Models

This table reports average annualized excess return and test results of standard asset pricing factor models (including CAPM, Fama-French 5 factors, and HXZ factors) across ten value and equal weighted age-sorted portfolios in the data. Portfolios are rebalanced at a quarterly frequency starting in July 1976 and ending in December 2016. Column'O' reports the portfolio consisting of firms with the oldest capital and Column 'Y' reports the portfolio consisting of firms with the youngest capital. Column 'OMY' reports the return difference of Portfolio 'O' and Portfolio 'Y'. The associated robust t-statistic is reported in brakets.

	Value weighted						Equal weighted					
	Y	2	5	9	O	OMY	Y	2	5	9	O	OMY
Panel A: Raw returns												
	Portfolio returns and Sharpe ratios						Portfolio returns and Sharpe ratios					
$E[R^e]$	-0.6	4.32	5.16	8.16	8.76	9.24	-3.09	3.69	10.58	12.74	12.21	15.29
$[t]$	-0.12	1.07	1.84	3.64	3.84	2.37	-0.63	0.90	3.06	3.90	3.74	5.57
SR	-0.03	0.17	0.31	0.55	0.59	0.45	-0.10	0.14	0.55	0.69	0.66	0.97
Panel B: CAPM												
	CAPM: MAE = 3.09						CAPM: MAE = 4.75					
Alpha	-11.29	-4.94	-2.00	2.42	3.24	14.53	-13.08	-5.16	3 .00	5.64	5.16	18.24
$[t]$	-3.94	-2.55	-1.52	1.78	2.12	4.58	-4.10	-1.96	1.29	2.75	2.52	7.45
MKT	1.49	1.28	1.00	0.80	0.76	-0.73	1.39	1.22	1.05	0.98	0.98	-0.41
$[t]$	23.12	25.01	22.13	15.09	13.12	-7.89	18.92	23.88	21.48	13.65	13.14	-5.45
R^2	0.72	0.72	0.79	0.69	0.65	0.28	0.59	0.62	0.68	0.69	0.66	0.15
Panel C: FF5 5-factor model												
	Fama-French 5: MAE=2.41						Fama-French 5: MAE=2.09					
Alpha	-6.06	-3.01	-4.42	-1.78	-0.81	5.25	-9.36	-5.04	-0.12	0.24	0.48	9.96
$[t]$	-2.72	-1.33	-3.98	-1.40	-0.72	2.37	-3.32	-2.17	-0.11	0.21	0.38	5.46
MKT	1.21	1.13	1.05	0.95	0.90	-0.32	1.10	1.05	0.99	1.02	0.99	-0.10
$[t]$	25.84	22.35	32.78	27.95	29.90	-6.15	20.14	24.52	31.21	34.74	28.16	-2.22
SMB	0.48	0.39	0.12	-0.08	0.04	-0.44	0.91	0.90	0.86	0.74	0.76	-0.15
$[t]$	4.70	3.47	2.56	-1.50	0.76	-4.43	8.23	12.54	12.75	14.64	13.01	-1.82
HML	0.07	-0.03	0.14	-0.04	0.22	0.15	0.26	0.29	0.31	0.45	0.48	0.23
$[t]$	0.70	-0.34	2.94	-0.47	3.67	1.55	1.50	2.20	3.34	5.36	5.31	2.08
RMW	-0.28	0.01	0.35	0.45	0.25	0.53	-0.57	-0.21	0.08	0.25	0.17	0.74
$[t]$	-2.49	0.10	5.28	7.11	3.07	4.67	-3.19	-1.77	0.96	3.27	2.12	6.03
CMA	-1.04	-0.53	-0.05	0.47	0.35	1.40	-0.75	-0.39	-0.03	0.15	0.04	0.79
$[t]$	-7.41	-4.84	-0.85	4.53	4.40	9.36	-2.33	-1.54	-0.25	1.37	0.33	3.69
R^2	0.81	0.77	0.80	0.78	0.70	0.60	0.76	0.78	0.86	0.89	0.86	0.48
Panel D: HXZ 4-factor model												
	HXZ test: MAE=1.79						HXZ test: MAE=2.26					
Alpha	-4.53	-2.15	-3.72	-2.47	0.48	5.01	-5.70	-1.38	2.02	1.98	2.40	8.10
$[t]$	-1.82	-1.01	-2.96	-1.79	0.38	2.08	-1.72	-0.46	1.02	1.09	1.33	3.84
MKT	1.26	1.16	1.03	0.94	0.85	-0.41	1.12	1.03	0.95	0.97	0.95	-0.17
$[t]$	25.19	21.54	25.53	27.32	23.58	-7.06	18.74	21.24	23.06	21.58	18.07	-3.46
ME	0.34	0.30	0.03	-0.11	-0.04	-0.38	0.71	0.71	0.70	0.59	0.60	-0.11
$[t]$	2.55	2.85	0.47	-2.24	-0.55	-3.71	4.33	5.36	5.77	4.81	4.64	-1.61
IA	-0.98	-0.56	0.08	0.49	0.57	1.55	-0.48	-0.18	0.27	0.65	0.56	1.04
$[t]$	-7.58	-5.86	1.32	6.37	5.19	9.84	-2.07	-0.95	2.16	5.15	4.55	5.35
ROE	-0.27	-0.04	0.18	0.34	0.00	0.26	-0.80	-0.54	-0.24	-0.13	-0.19	0.61
$[t]$	-2.81	-0.45	2.20	5.88	-0.01	1.94	-4.34	-4.02	-2.85	-1.21	-1.66	3.84
R^2	0.83	0.81	0.85	0.84	0.75	0.55	0.78	0.80	0.85	0.85	0.82	0.43

Table 7: Average Returns of Double Sort Portfolios

This table reports average annualized excess return across 5×5 value and equal weighted portfolios double sorted on investment rate and capital age (Panel A) , market equity and capital age (Panel B), and book-to-market ratio and capital age (Panel C). Portfolios are rebalanced at a quarterly frequency starting in July 1976 and ending in December 2016. Column'O' reports the portfolio consisting of firms with the oldest capital and Column 'Y' reports the portfolio consisting of firms with the youngest capital. Column 'OMY' reports the return difference of Portfolio 'O' and Portfolio 'Y'.

	Vaue weighted					Equal weighted				
	Age					Age				
	Y	M	O	OMY	[t]	Y	M	O	OMY	[t]
Panel A: Capital age and investment rate sorted portfolios										
L	-0.59	9.57	8.97	9.56	2.67	2.34	14.25	14.11	11.77	4.38
M	4.04	7.80	8.45	4.41	1.32	3.21	10.79	12.19	8.99	3.84
H	1.98	5.27	5.81	3.84	1.06	-2.44	7.31	12.10	14.54	5.25
H-L	2.56	-4.30	-3.16			-4.79	-6.94	-2.01		
[t]	0.73	-2.32	-1.42			-1.68	-3.14	-0.92		
Panel B: Capital age and size sorted portfolios										
L	-2.50	10.55	13.93	16.43	4.65	8.09	18.36	19.64	11.55	3.55
M	0.37	9.12	10.26	9.89	4.09	-2.30	9.49	11.03	13.32	5.81
H	4.75	7.41	8.03	3.29	0.98	2.99	8.04	9.36	6.37	2.09
H-L	7.25	-3.14	-5.90			-5.10	-10.33	-10.28		
[t]	1.49	-0.81	-1.61			-1.16	-2.92	-2.75		
Panel C: Capital age and book-to-market sorted portfolios										
L	2.87	6.53	3.05	0.18	0.04	-5.05	5.07	6.18	11.23	3.92
M	1.90	7.89	9.60	7.70	3.12	1.70	10.42	11.73	10.03	4.78
H	1.21	13.18	14.29	13.08	2.98	9.93	17.34	17.03	7.10	2.24
H-L	-1.66	6.65	11.24			14.98	12.27	10.85		
[t]	-0.29	2.04	3.31			4.24	4.55	3.47		

Table 8: Asset Pricing Tests with Double Sort Portfolios

This table reports annualized alphas of standard asset pricing factor models (including CAPM, Fama-French 5 factors, and HXZ factors) across 5×5 value and equal weighted portfolios double sorted on capital age on one hand and investment rate, market equity, and book-to-market ratio on the other. Panel A reports the CAPM risk-adjusted returns. Panel B reports the FF5 risk-adjusted returns. Panel C reports the HXZ risk-adjusted returns. Portfolios are rebalanced at a quarterly frequency starting in July 1976 and ending in December 2016. Column'O' reports the portfolio consisting of firms with the oldest capital and Column 'Y' reports the portfolio consisting of firms with the youngest capital. Column 'OMY' reports the return difference of Portfolio 'O' and Portfolio 'Y'.

	Vaue weighted					Equal weighted				
	Age					Age				
	Y	M	O	OMY	[t]	Y	M	O	OMY	[t]
Panel A: CAPM										
	CAPM Alphas					CAPM Alphas				
Capital age and investment rate sorted portfolios										
L	-10.25	2.03	1.91	12.16	3.52	-6.96	6.14	6.62	13.58	4.99
M	-5.37	1.16	3.03	8.40	2.88	-5.89	3.28	5.28	11.17	5.28
H	-8.04	-2.67	-1.44	6.60	2.08	-12.06	-0.68	4.77	16.83	6.77
H-L	2.21	-4.69	-3.35			-5.10	-6.82	-1.86		
[t]	0.63	-2.56	-1.45			-1.85	-3.34	-0.84		
Capital age and size sorted portfolios										
L	-10.76	3.59	7.46	18.22	5.64	-0.03	11.39	13.07	13.10	4.12
M	-9.73	1.09	2.97	12.71	6.32	-12.11	1.49	3.76	15.87	8.18
H	-4.95	0.71	2.64	7.58	2.80	-7.10	0.54	2.48	9.58	3.75
H-L	5.81	-2.88	-4.82			-7.07	-10.85	-10.59		
[t]	1.34	1.34	-1.39			-1.73	-3.18	-2.97		
Capital age and book-to-market sorted portfolios										
L	-7.50	-0.28	-2.79	4.71	1.40	-14.92	-3.09	-0.57	14.36	5.75
M	-7.13	1.05	3.77	10.90	4.86	-7.45	2.85	4.65	12.09	6.24
H	-8.55	5.48	6.43	14.98	3.75	1.65	9.80	9.85	8.20	2.68
H-L	-1.06	5.76	9.21			16.57	12.89	10.42		
[t]	-0.20	1.85	2.74			4.86	5.14	3.47		

Table 8: Asset Pricing Tests with Double Sort Portfolios (cont.)

	Vaue weighted					Equal weighted				
	Age					Age				
	Y	M	O	OMY	[t]	Y	M	O	OMY	[t]
Panel B: FF5 4-factor model										
	Fama-French 5 Alphas					Fama-French 5 Alphas				
Capital age and investment rate sorted portfolios										
L	-8.65	-2.41	-3.82	4.83	1.50	-3.96	3.40	1.97	5.93	2.10
M	-2.26	-1.57	-0.96	1.30	0.54	-5.22	-0.65	-0.07	5.15	3.09
H	-4.58	-4.90	-5.64	-1.06	-0.40	-10.12	-3.19	1.80	11.92	5.28
H-L	4.06	-2.48	-1.82			-6.16	-6.59	-0.16		
[t]	1.38	-1.50	-0.82			-2.38	-3.69	-0.08		
Capital age and size sorted portfolios										
L	-8.53	2.01	4.90	13.43	4.29	3.65	10.30	10.71	7.06	2.27
M	-8.95	-3.29	-2.82	6.13	4.42	-11.38	-2.81	-1.90	9.48	6.64
H	-0.12	-1.82	-1.18	-1.06	-0.52	-3.95	-2.87	-2.40	1.55	0.80
H-L	8.41	-3.83	-6.09			-7.60	-13.18	-13.11		
[t]	2.51	-1.50	-2.19			-2.11	-4.85	-4.27		
Capital age and book-to-market sorted portfolios										
L	-2.38	-2.66	-7.35	-4.97	-1.80	-12.03	-4.70	-4.45	7.57	3.79
M	-7.07	-1.96	-0.27	6.79	3.77	-6.38	-1.11	-0.56	5.81	3.72
H	-8.32	-0.11	0.60	8.92	2.38	2.67	6.10	4.51	1.83	0.60
H-L	-5.94	2.55	7.95			14.70	10.80	8.96		
[t]	-1.28	1.09	3.07			4.84	5.38	3.45		
Panel C: HXZ 4-factor model										
	HXZ Alphas					HXZ Alphas				
Capital age and investment rate sorted portfolios										
L	-4.45	-1.23	-3.07	1.39	0.41	1.66	7.28	4.56	2.91	1.00
M	-1.57	-1.01	-0.83	0.74	0.28	-1.64	1.27	1.58	3.22	1.80
H	-3.39	-4.37	-4.96	-1.56	-0.56	-7.02	-1.85	3.18	10.19	4.32
H-L	1.06	-3.15	-1.89			-8.67	-9.13	-1.39		
[t]	0.34	-1.88	-0.83			-3.36	-5.63	-0.67		
Capital age and size sorted portfolios										
L	-3.80	5.38	8.46	12.26	3.74	9.16	14.08	14.35	5.20	1.58
M	-6.51	-1.61	-1.47	5.04	3.04	-7.95	-0.68	-0.21	7.75	4.74
H	0.55	-1.36	-1.05	-1.60	-0.70	-2.80	-1.99	-1.49	1.31	0.61
H-L	4.35	-6.74	-9.51	-1.16		-11.96	-16.07	-15.84		
[t]	1.25	-2.84	-3.59			-3.32	-6.09	-5.34		
Capital age and book-to-market sorted portfolios										
L	-2.20	-2.98	-8.40	-6.21	-1.99	-10.13	-3.65	-4.20	5.93	2.62
M	-5.07	-1.01	0.11	5.18	2.70	-2.50	0.67	0.73	3.23	1.92
H	-3.48	4.69	4.46	7.94	2.09	8.55	10.47	8.37	-0.18	-0.06
H-L	-1.28	7.67	12.87			18.68	14.11	12.57		
[t]	-0.27	3.20	4.87			6.08	7.41	5.17		

Table 9: Cross-Sectional Regressions

This table reports the results of cross sectional regressions of individual stock excess returns on their lagged value and firms' characteristics. In Panel A, we run Fama-MacBeth regressions. The reported coefficient is the average slope from month-by-month regressions and the corresponding t-statistic is the average slope divided by its time-series standard error. The reported R-squared is the time-series average of the cross sectional R-squared. In Panel B, we run pooled OLS regressions with time fixed effects and standard errors clustered at the time level. All the control variables are divided by their unconditional standard deviation. The sample period is from 1977m7 to 2016m12.

Panel A: Fama-MacBeth

	[1]	[2]	[3]	[4]	[5]	[6]
Lagged return	-0.77	-0.79	-0.81	-0.79	-0.83	-0.87
[t]	-9.86	-10.61	-10.45	-10.14	-10.78	-11.74
Capital age (log)	0.41	0.43	0.32	0.36	0.37	0.28
[t]	6.67	7.47	5.30	5.39	6.57	5.26
Size (log)		-0.27				-0.27
[t]		-3.05				-3.40
BM (log)			0.38			0.24
[t]			6.59			4.45
IK				-0.18		-0.17
[t]				-4.43		-5.28
ROE					0.36	0.46
[t]					5.58	8.72
Observations	480	480	480	480	480	480
R^2	0.015	0.026	0.021	0.017	0.022	0.036

Panel B: Pooled OLS

	[1]	[2]	[3]	[4]	[5]	[6]
Lagged return	-0.85	-0.73	-0.89	-0.86	-0.88	-0.75
[t]	-35.33	-30.25	-35.72	-34.48	-35.00	-30.04
Capital age (log)	0.61	0.12	0.44	0.58	0.66	0.12
[t]	19.74	3.90	13.84	17.64	20.47	3.38
Size (log)		-3.43				-3.59
[t]		-62.35				-56.08
BM (log)			1.01			0.18
[t]			36.18			5.63
IK				-0.10		-0.03
[t]				-5.16		-1.53
ROE					0.13	0.41
[t]					4.96	15.73
Observations	924,533	924,533	892,972	901,488	875,025	868,275
R^2	0.143	0.149	0.147	0.145	0.146	0.152
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Price of Risk of Technology Adoption Shock

This table presents the estimates from a two-step GMM of the parameters of the stochastic discount factor

$$M_t = 1 - b_M \times \text{MKT}_t - b_{MACRO} \times \text{MACRO}_t,$$

In Panel A and Panel B we use the 10 capital age-sorted portfolios as test portfolios. In Panel C we use the 6 size and book-to-market Fama-French portfolios, the 17 Fama-French industry portfolios, and the 10 momentum portfolios as test portfolios. In Panel A we report the pricing error (α_i) and the sensitivity (β_i) of each portfolio to the different macroeconomic shocks implied by the two-factor models estimated in Panel B. In Panel B and Panel C we report the first-stage results of a GMM estimation of a two-factor and a three factor model, respectively. The two-factor model includes the market excess return and one macroeconomic shock, while the three-factor model includes the market excess return, the technology adoption shock, and one macroeconomic shock. For each estimated model, we report the estimated risk factor loadings, their corresponding t-statistics and the model's mean absolute error. The reported t-statistics are computed using the Newey-West procedure adjusted for four lags. All portfolios are value-weighted and the sample period is 1977q3 to 2014q4.

Panel A: Alphas and sensitivity to macroeconomics shock (capital age portfolios)

Portfolio		Tech	GDP	TFP	cay	Liquidity	Credit	Uncertainty
1	α_i	-0.072	-1.621	-1.798	-0.935	-2.369	-2.168	-2.631
	$[t]$	-0.183	-1.788	-1.866	-1.496	-3.537	-2.693	-4.168
	β_i	-0.036	-0.220	0.826	-0.844	-0.002	-0.054	-0.125
	$[t]$	-3.142	-1.677	1.383	-1.846	-0.040	-1.683	-0.750
2	α_i	-0.221	-0.615	-0.169	0.129	-0.401	-0.185	-0.301
	$[t]$	-0.279	-0.904	-0.200	0.224	-0.848	-0.329	-0.797
	β_i	-0.007	-0.065	0.564	-0.588	-0.009	-0.053	-0.387
	$[t]$	-0.525	-0.498	1.099	-1.273	-0.144	-1.153	-2.119
5	α_i	-0.326	-0.955	-0.174	-0.858	-0.429	-0.096	-0.022
	$[t]$	-0.653	-1.735	-0.275	-1.824	-1.557	-0.228	-0.087
	β_i	0.002	0.082	0.179	0.035	0.066	-0.022	-0.206
	$[t]$	0.229	1.217	0.490	0.189	2.335	-1.250	-2.115
9	α_i	0.612	0.377	-0.558	0.772	0.784	0.699	0.738
	$[t]$	1.151	0.796	-1.149	1.313	1.967	1.428	2.408
	β_i	0.003	0.044	-0.797	-0.213	0.036	-0.003	0.017
	$[t]$	0.430	0.610	-2.438	-1.331	1.010	-0.129	0.198
10	α_i	-0.254	0.420	0.986	1.136	1.048	1.706	1.195
	$[t]$	-0.480	0.836	1.128	1.432	2.131	2.897	3.075
	β_i	0.019	0.083	0.008	-0.253	0.037	-0.046	-0.106
	$[t]$	1.673	1.166	0.018	-1.369	1.390	-2.091	-1.134
OMY	α_i	-0.182	2.041	2.784	2.071	3.417	3.873	3.826
	$[t]$	-0.398	1.856	1.804	1.822	3.189	3.081	4.214
	β_i	0.055	0.303	-0.818	0.591	0.039	0.008	0.020
	$[t]$	2.734	2.096	-1.077	1.105	0.591	0.195	0.086

Table 10: Price of Risk of Technology Adoption Shock (cont.)

Panel B: GMM estimation with capital age sorted portfolios

	MKT	Tech	GDP	TFP	cay	Liquidity	Credit	Uncertainty
Two-factor Model								
b_{MKT}	0.173	0.192	0.133	0.123	0.443	-0.267	0.434	0.299
$[t]$	2.058	1.092	0.642	0.666	2.304	-0.993	2.313	2.380
b_{MACRO}		2.068	1.692	-2.059	1.861	0.856	1.007	0.452
$[t]$		2.814	2.186	-1.641	2.173	1.701	2.066	1.453
MAE	0.890	0.298	0.772	0.660	0.581	0.865	0.677	0.818
Three-factor Model								
b_{MKT}			0.188	0.165	0.285	-0.072	0.300	0.264
$[t]$			1.046	0.932	1.717	-0.206	1.476	1.220
b_{TECH}			2.017	1.811	1.653	2.036	1.939	2.042
$[t]$			2.693	2.483	2.453	2.714	2.614	2.897
b_{MACRO}			0.109	-1.006	0.672	0.513	0.421	0.258
$[t]$			0.147	-1.315	1.287	0.803	0.826	0.426
MAE			0.289	0.138	0.186	0.258	0.240	0.281

Panel C: GMM estimation with different test assets

	MKT	Tech	GDP	TFP	cay	Liquidity	Credit	Uncertainty
Two-factor Model								
b_{MKT}	0.233	0.216	0.227	0.226	0.332	0.362	0.372	0.411
$[t]$	0.609	0.558	0.603	0.474	0.567	0.607	0.559	0.580
b_{MACRO}		0.852	0.277	-0.924	0.839	-0.247	0.504	0.621
$[t]$		2.618	0.860	-1.978	1.615	-0.622	2.280	1.982
MAE	0.609	0.558	0.603	0.474	0.567	0.607	0.559	0.580
Three-factor Model								
b_{MKT}			0.213	0.212	0.320	0.448	0.360	0.387
$[t]$			2.044	1.713	2.400	1.691	2.864	3.018
b_{TECH}			0.826	0.698	0.909	0.943	0.904	0.804
$[t]$			2.411	1.587	2.455	2.997	2.267	2.012
b_{MACRO}			0.182	-0.872	0.893	-0.448	0.527	0.595
$[t]$			0.519	-1.844	1.501	-0.857	1.569	1.434
MAE			0.553	0.411	0.459	0.508	0.450	0.472

Table A1: Capital Age–Sorted Portfolios (Alternative Capital Age Measure)

Portfolios are sorted in deciles calculated using the alternative measure of capital age and are rebalanced at a quarterly frequency starting in July 1977 and ending in December 2016. We report value weighted results. Panel A reports the time series average of monthly excess returns across ten age–sorted portfolios together with the corresponding t-statistics and Sharpe Ratio for the two bottom, the fifth, and the two top capital age sorted portfolios. Columm *O-Y* reports the difference between the tob and bottom portfolios. Panel B reports the risk-adjusted returns using the CAPM. For the CAPM asset pricing model, we report the risk-adjusted return (alpha), the loading on the market factor, the adjusted R^2, and the mean absolute error. The reported returns are annualized versions of their monthly counterpart and all t-statistics are calculated using the Newey-West autocorrelation and heteroskedasticity-consistent standard errors with 6 lags.

	Young	2	5	9	Old	O-Y
Panel A: Portfolio returns and Sharpe ratios						
$E[R^e]$	2.64	4.92	6.00	8.16	9.24	6.60
t-stat	0.62	1.20	1.97	3.47	4.50	1.89
SR	0.11	0.21	0.33	0.54	0.68	0.10
Panel B: CAPM alphas						
mae = 3.71						
α	-7.12	-4.33	-1.65	2.22	4.08	11.19
t-stat	-2.93	-2.05	-1.22	1.43	3.29	3.67
MKT	1.36	1.28	1.06	0.82	0.72	-0.64
t-stat	22.93	23.88	31.70	17.07	17.01	-7.30
R^2	0.70	0.70	0.82	0.71	0.65	0.25

Table A2: Capital Double Sorted Portfolios (Alternative Capital Age Measure)

Portfolios are independently sorted in three capital age and three investment rate categories (Panel A) using the 20th and 80th percentiles of the cross-sectional distribution of the corresponding sorting variable at the end of each quarter 6 months prior to portfolio formation. Panel B reports the results for portfolios sorted on capital age and size, while Panel C reports the results for portfolios sorted on capital age and book–yo–market. The size categories are evaluated the month prior to portfolio formation. Portfolios are rebalanced at a quarterly frequency starting in July 1977 and ending in December 2016. We report value weighted results. Each panel reports the time series average of monthly excess returns and the risk–adjusted returns across the nine portfolios together with the difference between the top and bottom capital age categories (O-Y) and difference between the top and bottom category of the other sorting variable. The reported returns are annualized versions of their monthly counterpart and all t-statistics are calculated using the Newey-West autocorrelation and heteroskedasticity-consistent standard errors with 6 lags.

Panel A: Capital Age and Investment Rate Sorted Portfolios

	Young	Medium	Old	O-Y	t-stat	Young	Medium	Old	O-Y	t-stat
	Excess Returns					CAPM α				
Low IK	5.11	9.78	8.5	3.39	1.14	-3.67	2.36	1.52	5.19	1.79
3	5.93	7.38	8.66	2.73	0.8	-2.97	0.71	3.26	6.23	2.15
High IK	3.12	4.98	6.18	3.06	0.89	-6.77	-3.08	-1.39	5.38	1.63
H-L	-1.99	-4.8	-2.32			-0.95	-2.7	-1.11		
	-0.61	-2.27	-0.93							
	FF5 α					HXZ α				
Low IK	-7.37	-2.36	-4.01	3.36	1.23	-5.04	-0.76	-3.77	1.27	0.46
3	-0.11	-2.13	-0.76	-0.65	-0.27	0.7	-1.55	-0.6	-1.3	-0.5
High IK	-3.27	-4.82	-5.32	-2.04	-0.74	-2.23	-4.24	-4.21	-1.97	-0.67
H-L	4.09	-2.46	-1.31			2.81	-3.48	-0.44		
	1.39	-1.36	-0.52			0.95	-1.88	-0.17		

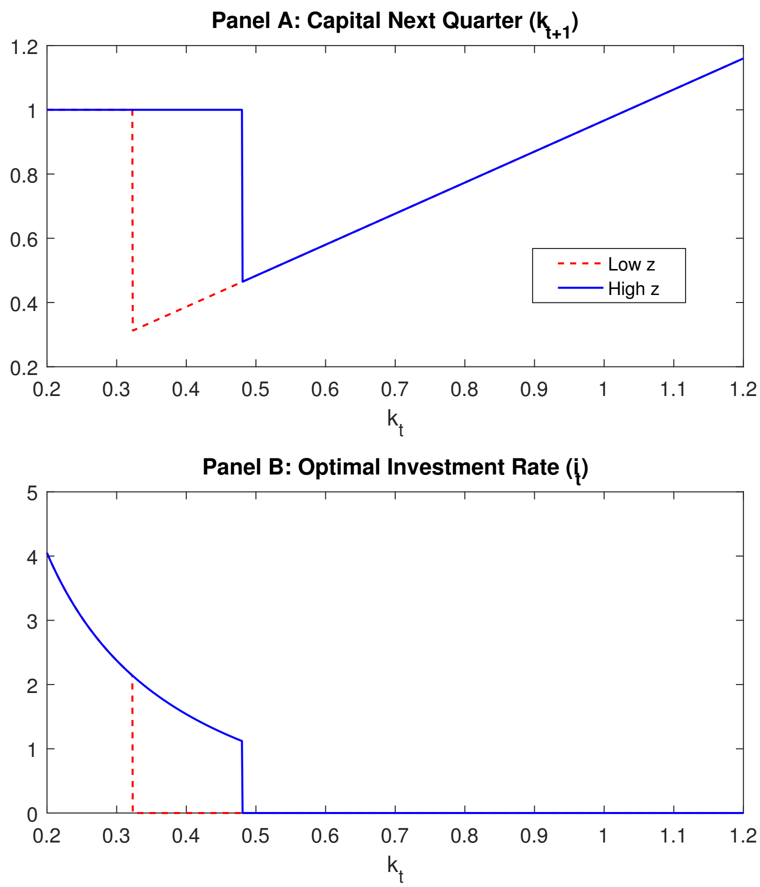
Panel B: Capital Age and Size Sorted Portfolios

	Young	Medium	Old	O-Y	t-stat	Young	Medium	Old	O-Y	t-stat
	Excess Returns					CAPM α				
Small	-0.06	9.78	14.22	14.28	3.95	-8.43	3.03	7.44	15.87	4.89
3	0.59	8.71	10.76	10.17	4.02	-9.58	0.57	3.69	13.27	6.44
Big	6.15	7	8.17	2.02	0.62	-2.85	0.26	2.81	5.66	2.1
BMS	6.2	-2.77	-6.05			5.58	-2.76	-4.63		
	1.23	-0.78	-1.55			1.24	-0.83	-1.23		
	FF5 α					HXZ α				
Small	-7.02	1.58	5.06	12.07	3.77	-2.26	4.66	9.04	11.3	3.44
3	-8.77	-3.76	-1.85	6.93	4.81	-6.34	-2.03	-0.52	5.83	3.39
Big	1.36	-2.32	-1.04	-2.4	-1.22	1.71	-1.82	-0.91	-2.61	-1.16
BMS	8.38	-3.9	-6.09			3.97	-6.49	-9.94		
	2.46	-1.7	-2.01			1.15	-2.98	-3.49		

Panel C: Capital Age and Book-to–Market Sorted Portfolios

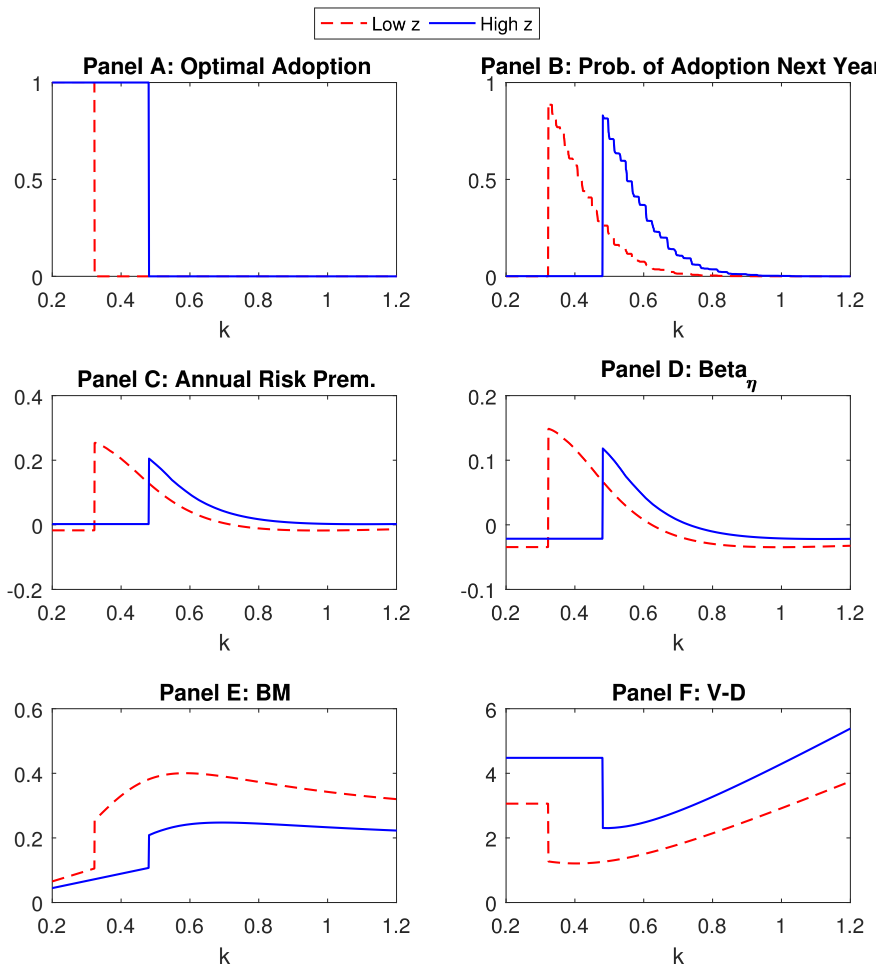
	Young	Medium	Old	O-Y	t-stat	Young	Medium	Old	O-Y	t-stat
	Excess Returns					CAPM α				
Growth	4.43	5.9	4.38	-0.05	-0.01	-5.36	-0.96	-1.54	3.82	1.12
	4.16	7.63	9.56	5.4	2.13	-4.63	0.78	3.83	8.46	3.78
Value	5.45	12.3	14.83	9.38	2.06	-4.43	4.51	7.08	11.51	2.83
VMG	1.02	6.4	10.45			0.92	5.46	8.62		
	0.18	2.02	3.14			0.17	1.8	2.65		
	FF5 α					HXZ α				
Growth	-0.78	-3.35	-6.17	-5.39	-1.95	1.06	0.68	4.08	3.02	0.94
	-4.38	-2.32	-0.08	4.3	2.34	-3.06	0.06	5.26	8.32	4.24
Value	-5.37	-0.68	1.45	6.82	1.76	-9.09	7.54	8.77	17.86	4.62
VMG	-4.58	2.67	7.62			-10.15	6.86	4.69		
	-0.93	1.19	2.96			-1.94	2.69	1.59		

Figure 1: Investment policy functions



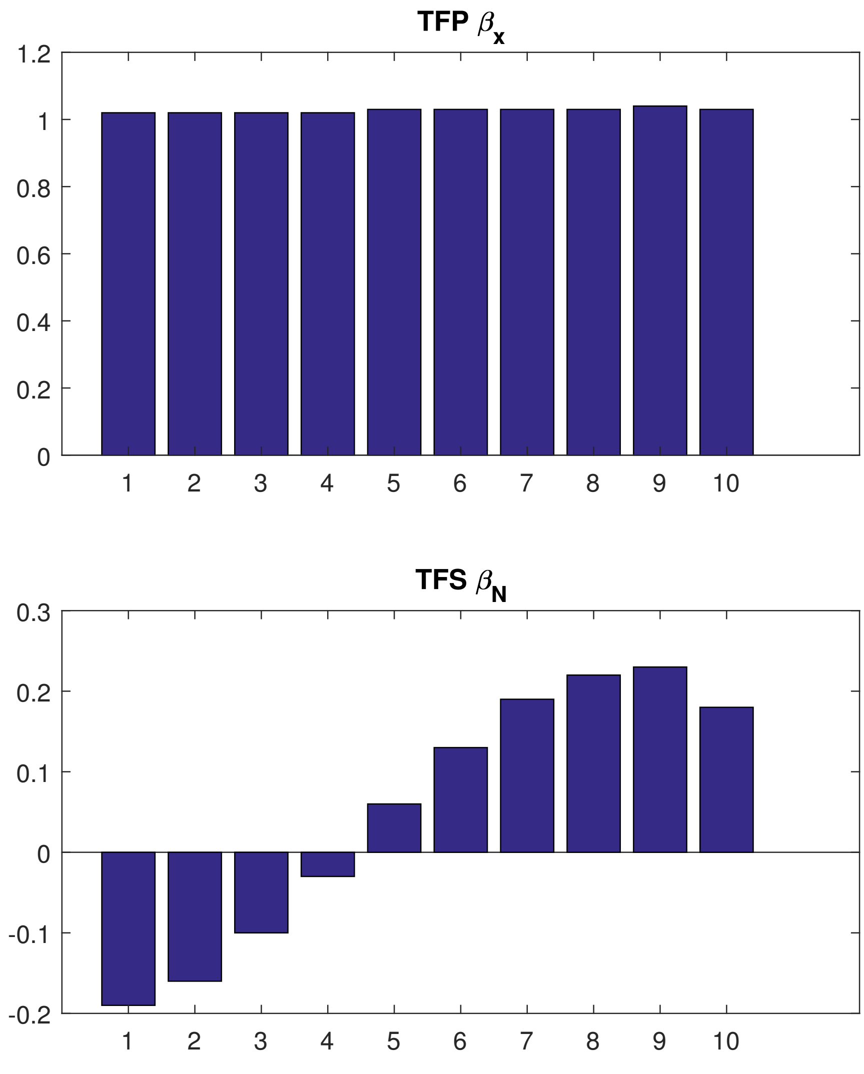
This figure compares the optimal investment policy for high and low productive (z) firms. We fix the detrended aggregate productivity and the detrended technology frontier at their long run means. Panel A reports the optimal capital in next period as a function of the capital in this period for both high and low productive firms. Panel B reports the optimal investment rate (I/K) as a function of the capital for both high and low productive firms.

Figure 2: Policy functions



This figure reports adoption, the probability of adoption next year, the annual risk premium of a stock, the beta to the technology frontier shock, book-to-market ratio, *ex*-dividend firm value $(V - D)$ as functions of the detrended capital (k) for high and low productive (z) firms. We fix the detrended aggregate productivity and the detrended technology frontier at their long run means.

Figure 3: Model predicted capital age portfolio betas to the aggregate productivity shock and the technology frontier shock



This figure reports the model predicted betas to the aggregate productivity shock (Δx_{t+1}) and the technology frontier shock ($\sigma_N \eta_{t+1}$) across ten value weighted portfolios sorted on capital age.