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

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Abstract

We study the impact of technology adoption on asset prices in a dynamic model that features a stochastic technology frontier. In equilibrium, firms operating with old capital are riskier because costly technology adoption restricts their flexibilities in upgrading to the latest technology, making them more exposed to technology frontier shocks. Consistent with the model predictions, a long-short portfolio sorted on firm-level capital age earns an average value-weighted return of 9% per year among U.S. public companies. A proxy for technology frontier shocks captures the variation of the capital age portfolios with a positive risk price, corroborating the model mechanism.

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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 technology frontier 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 and more productive capital has accelerated significantly over the past 30 years, from 2 percent per year in the 1960s to 4.5 percent in the 1990s (See, e.g., Gordon (1990) and Cummins and Violante (2002)). In this paper, we study how the time-variation of the aggregate technology frontier affects firms' asset prices and real quantities. We show empirically and through the lens of a production-based model that firms' technology adoption decisions have a significant impact on the cross section of stock returns.

We start by developing a dynamic model that features a stochastic technology frontier and costly technology adoption. In the model, the technology frontier, which all firms have access to, follows a stochastic process driven by a systematic shock[1], similar to Abel and Eberly (2012). Facing a stochastic technology frontier and the standard aggregate and firm-specific productivity shocks, firms optimally choose to adopt the latest capital or to keep operating with the existing vintage, which will become obsolete (i.e., less productive) over time. The benefit of adopting the latest technology is a more efficient installed capital. However, firms incur costs when adopting technology as in Cooper, Haltiwanger, and Power (1999).

Adoption costs arise because not all firms' existing expertise (human capital or workers' skills) can be applied to the new technology. In the model, the adoption process involves gross investment and a fixed adoption cost. Gross investment is larger when the firm's capital is further away from the technology frontier since current capital cannot be used for the operation of the new technology. Fixed adoption costs capture the cost of learning a new technology, workers training cost, the destruction cost of old organizational capital, etc. This feature delivers lumpiness in the technology adoption policy implying that firms with higher productivity or firms with older and less efficient capital are more likely to adopt the

[1] We assume the aggregate technology frontier shock carries a positive price of risk, for which we provide evidence in the empirical analysis.

latest technology. Through this channel, the model endogenously generates a cross-section of firms with different capital age (i.e., different technical efficiency), measured as the number of periods since last adoption.

Costly technology adoption restricts 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. The key insight is that firms that adopt the latest technology or operate with the more efficient capital (i.e., young capital age firms) are less risky than non-adopting firms operating with less efficient capital (i.e., old capital age firms). The economic mechanism is as follows. Young capital age firms are productive firms that operate with the recently upgraded capital and are close to the technology frontier. They have low probabilities of adopting going forward, because the benefit of replacing their already-efficient capital does not outweigh the adoption costs. As a result, their continuation value is less tied to the fluctuations of the aggregate technology frontier. In contrast, old capital age firms are low productivity firms that are far from the technology frontier. They are in need of upgrading the obsolete technology, however, in equilibrium the adoption costs limit their ability to do so. Thus, their continuation value is more exposed to the aggregate technology frontier shock. As a result, young capital age firms earn lower expected returns than old capital age firms. Linking capital age to the cross-sectional returns, the model generates asset pricing implications that are distinct from those of standard investment-based asset pricing models (e.g., Zhang (2005)) where capital vintage is homogeneous across firms and there is no distinction between new and old capital.

Through several comparative static exercises, we show that the existence of technology adoption costs is important for the good quantitative fit of the model. When technology adoption is free of costs, firms' average capital age drops substantially from 20 quarters in the benchmark calibration to 3 quarters. Moreover, the capital age spread (the return differential between old capital age and young capital age firms) becomes tiny, close to 0% per annum vs 9.6% in the benchmark economy and 9.5% in the data. This is intuitive. Without adoption costs, all firms can adopt the frontier technology freely, resulting in a counterfactually low average capital age. This in turn implies that all firms can use the same efficient capital and have the same exposure to the technology frontier shock, causing the cross sectional risk dispersion to be tiny. In summary, our results suggest that costly adoption decisions can have a significant impact on the cross-sectional variations of stock returns.

Empirically, we recursively estimate a measure of capital age using firm–level investment data of the U.S. public companies following the methodologies developed in the empirical industrial organization literature (e.g., Salvanes and Tveteras (2004)). Given that firms' capital age is not readily observable in the data, this exercise allows us to study the links between technology adoption and stock returns directly. We show that firms with young capital age earn lower average returns than firms with old capital age, consistent with the model's prediction. 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, a one standard deviation increase in the firm's current (log) capital age is associated with an increase of 4.8 percentage points in the firm's annual future stock return. We show that the predictability of capital age remains robust 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 firms' returns with different capital age to the aggregate stock market factor 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 alpha of the capital age return spread is larger than the capital age return spread itself. The model replicates the failure of the CAPM. According to the model, the aggregate stock market is mostly driven by the standard aggregate productivity shock but less correlated with the aggregate technology frontier shock, which solely drives the capital age return spread in the cross section. In addition, we show that other standard asset pricing factor models (e.g., Fama and French (2015)) cannot explain the capital age spread as well.

Lastly, we construct a proxy for the aggregate technology frontier shock by using the introduction of new technology standards. Specifically, we follow Baron and Schmidt (2017) and use the change in the number of technology standards released by both the U.S. and International Standard Setting Organizations (SSOs), which we interpret as a proxy for aggregate shocks to the technology frontier[2]. We show that the exposure to this proxy well captures the cross-sectional variation in stock returns across the capital age portfolios. In

[2]Baron and Schmidt (2017) show that the introduction of new technology standards anticipates the adoption of new technologies and positively correlates with future productivity gains.

particular, old capital firms load more on this proxy than young capital firms, consistent with the model. In addition, using a variety of test portfolios including size, book-to-market, momentum and industry portfolios, we show that the aggregate frontier shock proxy is positively and significantly priced. This finding provides support for the model's assumption that the aggregate frontier shock carries a positive risk price. Furthermore, the aggregate technology frontier shock proxy is not subsumed by other macroeconomic shocks that have explanatory power for the cross-section of stock returns. Taken together, our results show that technology frontier shocks are a source of systematic risk that is positively priced by investors.

The paper proceeds as follows. Section 2 discusses the related literature. Section 3 presents a dynamic model economy with technological shocks and costly technology adoption. Section 4 reports model-implied links between firms' capital age and the cross section of expected stock returns and also provides a detailed analysis of the economic mechanisms driving the model's results. Section 5 describes the construction of the firm-level capital age measure and its properties. Section 6 reports the empirical links between the capital age, systematic risk, and the cross sectional returns. Finally, Section 7 concludes. The Appendix provides additional results and robustness checks.

2 Related literature

This paper is related to the literature that examines the links between technological shocks and asset prices. Albuquerque and Wang (2008) use investment-specific technological change to examine the implications of imperfect investor protection for asset prices and welfare. Pastor and Veronesi (2009) investigate technological revolutions and aggregate stock price movements by focusing on the uncertainty of technological revolutions as the driving force for the stock price "bubbles". Lustig, Syverson and Van Nieuwerburgh (2011) explore the impact of technological change on the inequality of managerial compensation and the labor market reallocation. Papanikolaou (2011), Kogan and Papanikolaou (2014), and Garlappi and Song (2016) study the effect of investment-specific technological shocks on asset prices and real quantities. We show that our aggregate technology frontier shock proxy remains significantly priced after controlling for the investment-specific technology shock, implying that these two technological shocks capture different aggregate risks in the economy. Garleanu, Panageas and Yu (2012) examine the asset pricing implications of technological growth with both small productivity shocks and large innovations. Kung and Schmid (2015) study the implications of endogenous technological growth on asset prices and aggregate quantities. We differ from these works by concentrating on the relationship between firm-level technology adoptions of the frontier capital and the cross-sectional stock returns. Furthermore, we construct a measure of firms' capital age and show that old capital age firms are riskier empirically.

A related literature which studies asset prices in production economies has primarily focused on links between homogeneous capital across vintage and expected stock returns. Zhang (2005) investigates the value premium in a model with asymmetric capital adjustment costs and time-varying price of risk; however in Zhang (2005) capital is homogeneous across vintages. Another example with a model of homogeneous capital is Imrohoroglu and Tuzel (2014) who show that high productivity firms are less risky. We differ from Zhang (2005) and Imrohoroglu and Tuzel (2014) by allowing capital age and efficiency to vary over time and across firms, and hence bring new theoretical insights in asset pricing, which we confirm empirically as well.

Our work is also related to Ai, Croce and Li (2013), Ai, Croce, Diercks, and Li (2017) and Liao and Schmid (2017) who explore asset pricing implications in models with heterogenous vintage capital. Similar to us, Ai, Croce and Li (2013) show that firms with old capital vintage are riskier, but they emphasize a different economic mechanism. In their model, older firms are more exposed to aggregate productivity shocks because they adopt well-established technologies on a large scale; furthermore Ai, Croce, Diercks, and Li (2017) endogenize the empirical findings in Ai, Croce and Li (2013) through rational-but-slow perpetual learning mechanism. Different from these two papers, we explore a different source of systematic risk, i.e., fluctuations in the aggregate technology frontier (different from aggregate productivity shocks). Our mechanism hinges on costly technology adoption that makes old capital firms riskier. Liao and Schmid (2017) study the impact of technological adoptions on the supply of collateral and the joint dynamics of firms' credit and risk premia. We complement Liao and Schmid (2017) by directly studying the cross-sectional asset pricing implications of technology adoption.

The empirical methodology to measure a firm's capital age closely follows the industrial organization literature. Specifically, we follow Salvanes and Tveteras (2004) who use the time profile of investment expenditures to construct a measure of capital age in a panel of

Norwegian manufacturing plants[3]. We contribute to this literature by measuring capital age using the time profile of investment expenditures for a large set of U.S. publicly traded companies and studying the asset pricing implications.

3 The model

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

3.1 Production technology

Firms use their physical capital (K_t) to produce a homogeneous good (Y_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 log growth rate and volatility of aggregate productivity, respectively.

Firm-specific productivity follows an 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

[3] The capital age measurement in Salvanes and Tveteras (2004) builds on Mairesse (1978), who estimates capital age for a sample of French manufacturing firms. Hulten (1991) describes the challenges posed by the measurement of a firm's capital age.

all firms in the economy and independent of ε_{t+1}^{x}, and $\bar{z}$, ρ_z, and σ_z are the long run mean, autocorrelation, and conditional volatility of firm-specific productivity, respectively.

3.2 Costly technology adoption

We denote the stock of general and scientific technology of the entire economy as N_t. It captures new production technologies embodied in latest equipment and machines, which generates productivity gains. 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, σ_N is the volatility and η_t denotes an i.i.d standard normal random variable. Note that we assume the technology frontier at $t+1$ is determined by the shock (η_t) at time t so that there is no built-in uncertainty in the gross investment at t. As we describe in detail in Equation (6) below, gross investment (I_t) at t depends on N_{t+1} if a firm adopts the latest technology.

Given the aggregate and firm-specific productivities (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 continues 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 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 at all 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 time 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 is 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, but it is costly to do so. We assume that technology adoption costs, C_t, are given by

$$C_t = \begin{cases} 0 & \text{if} \quad \phi_t = 0 \\ X_t \left(f_a K_t + I_t\right) & \text{if} \quad \phi_t = 1 \end{cases} . \tag{7}$$

The adoption costs consist of two parts: a fixed cost ($f_a K_t$) where f_a is a constant with $f_a > 0$ and gross investment (I_t). Here, the fixed cost (as in Cooper, Haltiwanger, and Power 1999) captures the cost of learning the 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. Gross investment (I_t) captures the amount of gross investment that firms need to take on so as to reach the frontier. Lastly, the cost per unit of investment (X_t) varies over time and it is driven by aggregate productivity as in Jermann (1998) and Eisfeldt and Papanikolaou (2013). Under this assumption, gross investment grows at the same rate as aggregate output so that the detrended model is stationary.

Notably the fixed investment cost in Equation (7) also causes asynchronous technology adoption as in Jovanovic and Stolyarov (2000). That is, 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 (z_t) and capital stock (K_t), more productive (high z_t) firms and firms with less efficient capital (small K_t) are more likely to adopt the new technology, while less productive (low z_t) firms and firms with more efficient capital (large K_t) are more likely to find the the adoption too costly relative to its benefit and choose to keep operating 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 that firms need to pay regardless of adoption decisions.[4]

3.3 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:

$$\log M_{t,t+1} = -r_f - \frac{1}{2}\lambda_\varepsilon^2 - \frac{1}{2}\lambda_\eta^2 - \lambda_\varepsilon \varepsilon_{t+1}^x - \lambda_\eta \eta_{t+1}. \quad (8)$$

The sign of the risk factor loading parameters (λ_ε and λ_η) is positive. The specification $\lambda_\varepsilon > 0$ is consistent with most equilibrium models (e.g., Jermann(1998)). Low aggregate productivity states are associated with low output and thus low consumption and high marginal utility. The specification $\lambda_\eta > 0$ is consistent with the empirical findings that times of technological progress are associated with an increase in consumption and output and hence are lower marginal utility states. We also provide empirical support from asset prices in Section 6.5. r_f denotes the continuously compounded risk-free rate which is assumed to be a 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. Note that the moment condition $\mathrm{E}[M_{t,t+1}] = e^{-r_f} = 1/R_f$ is satisfied.

The firm maximizes shareholders' value by choosing to adopt the frontier technology

[4] We assume that the fixed production costs grow at the same rate as the rest of the economy so that the model is stationary after removing the stochastic trend.

$(\phi_t = 1)$ or keep using its existing 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).

3.4 Risk and expected stock return

In the model, risk and expected stock returns are determined endogenously along with firms' value-maximization. Using the value function, we obtain

$$\begin{aligned} V_t &= D_t + \mathrm{E}_t\left[M_{t,t+1}V_{t+1}\right] && (9) \\ &\Rightarrow 1 = \mathrm{E}_t\left[M_{t,t+1}R_{t+1}\right], && (10) \end{aligned}$$

where Equation (9) is the Bellman equation for the value function and Equation (10) follows from the standard formula for stock return $R^s_{t+1} = V_{t+1}/\left[V_t - D_t\right]$.

Substituting the stochastic discount factor from Equation (8) into Equation (10), and using some algebra, yields the following equilibrium asset pricing equation:[5]

$$\mathbb{E}_t\left[r^e_{t+1}\right] = \lambda_\varepsilon \times \mathrm{Cov}\left(r^e_{t+1}, \varepsilon^x_{t+1}\right) + \lambda_\eta \times \mathrm{Cov}\left(r^e_{t+1}, \eta_{t+1}\right) \quad (11)$$

in which $r^e_{t+1} = R^s_{t+1} - R_f$ is the stock excess return.

According to Equation (11), the equilibrium risk premiums in the model are determined by the endogenous covariances of the firm's excess stock returns with the two aggregate shocks (quantity of risk) and by the loading of the stochastic discount factor on the two risk factors (λ_ε and λ_η) in Equation (8). The pre-specified positive sign of the loadings imply that, all else equal, assets with returns that have a high positive covariance with the aggregate productivity shock are risky and offer high average returns in equilibrium.

[5] This derivation is standard. Equation (10) implies $\mathbb{E}_t\left[M_{t,t+1}\left(R^s_{t+1} - R_f\right)\right] = 0$ because $\mathbb{E}_t\left[M_{t,t+1}\right]R_f = 1$. Using a first-order log-linear approximation of the SDF $M_{t,t+1}$ defined in Equation (8), and applying the formula for covariance $Cov(X,Y) = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$ to the previous equation, plus some algebra, yields Equation (11).

Similarly, all else equal, assets with returns that have a high positive covariance with the aggregate technological frontier shock are risky and offer high average returns in equilibrium.

4 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 detrended capital k_t; (ii) the firm–level productivity z_t; and (iii) the technology frontier shock η_t. Because the functional forms of the value function and policy functions are not available analytically, we solve for these functions numerically. Appendix A1 detrends the model. Appendix A2 provides a description of the solution algorithm 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 initial conditions, 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. The latter variable is determined by optimal adoption decisions before t. Then, using this distribution of firms as initial condition, we simulate 5,000 firms and 120 quarters to be consistent with the sample length in the data. 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 4.3.

4.1 Calibration

Stochastic processes: We set the quarterly average log growth of the technological frontier (g_N) equal to 0.02/4, consistent with the estimate in Greenwood, Hercowitz and Krusell

(1997).[6] In the model, the aggregate productivity shock x_t is essentially a profitability shock. We set the quarterly average log growth of aggregate productivity (g_x) equal to 0.012/4 to match the average growth of aggregate profits and the quarterly volatility of the aggregate productivity shock to be $\sigma_x = 0.047$ 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 $\sigma_N = 0.0775$ to match the standard deviation of capital age in the data. 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 $\bar{z} = -1.73$ which implies that the average physical capital scaled by the technology frontier (k_t) across firms is around 0.7. To calibrate the persistence ρ_z and conditional volatility σ_z of firm-specific productivity, we restrict these two parameters using their implications on the degree of dispersion in the cross-sectional distribution of firms' stock return volatilities. We set $\rho_z = 0.97^3$ and $\sigma_z = 0.18$, which implies an average annual volatility of individual stock returns of 43%, close to the data counterpart at 49%.

Firm's technology: The quarterly capital depreciation rate (δ) is set to 0.025 as in Jermann (1998). The fixed cost of technology adoption (f_a) 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 larger the average capital age. We set the fixed cost of technology adoption, f_a, equal to 3.4 to match the average capital age in the data. The model implied average capital age is 20 quarters, close to the average age of 23 quarters in the data. It also implies that the correlation between capital age and investment is -0.22, close to the value of -0.24 in the data. The fixed operating cost (f_o) mainly affects the cross-sectional correlation between capital age and book-to-market ratio. We set $f_o = 0.06$ implying the cross-sectional correlation between capital age and book-to-market ratio of 0.16, close to 0.19 in the data.

Pricing kernel: The quarterly real risk-free rate is chosen to match the data $r = 0.022/4$.

[6] Because the growth rate of technology frontier g_N is not directly available in the data, we choose to calibrate it following the investment specific technological change as in Greenwood et al (1997), The quantitative implications of the model remain unchanged with different values of the growth rate g_N.

Given the calibrated volatilities of aggregate shocks, we set the price of aggregate risk to be $\lambda_\varepsilon = 5\sigma_x = 0.2350$ and the price the technology risk to be $\lambda_\eta = 5\sigma_N = 0.3875$ to match the average excess stock market return and the Sharpe ratio. This implies an average annual market excess return of 5.8% and a Sharpe ratio of 36%, close to their empirical counterparts.

4.2 Properties of model solutions

In this section, we discuss the policy functions of interest including the optimal adoption decision, the capital age, and the model implied risk premium. Figure 1 depicts these policy functions with all exogenous shocks set at their long run values.

4.2.1 Optimal Adoption and Capital Age

Panel A in Figure 1 reports the optimal technology adoption policy (ϕ_t) as a function of detrended capital k_t. ϕ_t is equal to 1 if the firm adopts the technology frontier capital and 0 otherwise. Note that after detrending, the optimal technology frontier capital takes the value of 1.[7] Given the firm-level productivity, the optimal adoption policy implies a threshold value for the current capital such that firms optimally choose not to adopt and operate with the existing capital ($\phi_t = 0$) when the current capital k_t is efficient and close to the frontier (i.e., larger than the threshold value). If the current capital k_t is obsolete and far away from the frontier (i.e., smaller than the threshold value), firms adopt the frontier capital ($\phi_t = 1$).

To analyze the relationship between capital age and current capital, we define the capital age of a firm operating with the capital on the technology frontier as zero (the detrended capital k_t of the firm is 1), and the capital age of a non-adopting firm as the number of quarters since last adoption. Then we derive in the model the relationship between the

[7]When a firm adopts at t, its detrended capital next period $k_{t+1} = 1$. In the model, we do note that a small fraction of firms adopted at $t-1$ may operate on k_t slightly higher than 1 when there is a large negative shock to the technology frontier at t. But these firms do not drive our main results.

expected capital age, $\mathrm{E}[T]$, and the log capital level $\log k_t$ as[8]

$$\mathrm{E}[T] = \frac{\log k_t}{\log(1-\delta) - g_N}. \tag{13}$$

Panel B reports the expected capital age as a function of detrended capital k_t. The expected capital age decreases in current capital k_t. Intuitively, firms using capital closer to the frontier ($k_{t+1} = 1$) have younger capital age and are more efficient, whereas firms that operate with capital further away from the frontier have old capital age and are less efficient. Therefore, the model endogenously generates a broad spectrum of firms with heterogeneous capital age.

Panel C reports the probability of adoption next year which is a key driver of the endogenously determined firm-level risks in the cross section. Given the optimal adoption policy function $\phi(z_t, \eta_t, k_t)$, we compute the probability of adoption next period as

$$\mathrm{Prob}_t[Adoption_{t+1}] = \mathrm{E}\left[\phi(z_{t+1}, \eta_{t+1}, k^*_{t+1})|z_t, \eta_t, k_t\right],$$

where k^*_{t+1} denotes the optimal capital next period. We use this equation recursively to obtain the probability of adoption for the next four quarters and approximate the probability of adoption next year by taking the sum.[9] Panel C reports the probability of adoption next year as a function of the detrended capital. The adoption probability decreases in current capital. Intuitively, firms with efficient capital that are closer to the frontier ($k_t = 1$) are less likely to adopt. Comparing with Panel A, we observe that the adoption probability rises to 1 when the detrended capital approaches the threshold of adoption. Combining with Panel B, the adoption probability is increasing in capital age. Namely, old capital firms are more likely to adopt than young capital firms.

[8] Iterating the detrended capital dynamics in Equation (30) in the Appendix A1, we can solve for the capital age (T) of a non-adopting firm as a function of log current capital and past technology frontier shocks since last adoption when $k_{t-T} = 1$ as follows

$$\log k_t = T\log(1-\delta) - g_N T - \sigma_N \sum_{j=1}^{T} \eta'_{t-j}. \tag{12}$$

Taking expectation on both sides of the above equation leads to Equation (13).

[9] Admittedly, the simple sum is not exactly the probability of adoption next year due to the possibility of multiple adoptions within a year. But this possibility is tiny under the fixed adoption cost.

4.2.2 Risk and expected return

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

$$R_{t+1} = \frac{V_{t+1}}{V_t - D_t} = \frac{v_{t+1}}{v_t - d_t} e^{g_N + \sigma_N \eta_t + \Delta x_{t+1}}. \tag{14}$$

The annual risk premium is computed as four times the quarterly risk premium

$$\mathrm{E}_t \left[R_{t+1}\right] - r_f = \mathrm{E}_t \left[\frac{V_{t+1}}{V_t - D_t}\right] - r_f. \tag{15}$$

Panel D in Figure 1 plots the annual risk premium of a stock as a function of the detrended capital. The stock risk premium decreases in current capital for non-adopting firms. That is, firms that are closer to the frontier with more efficient (i.e., higher values of) capital and lower capital age offer less expected returns.

We then decompose the risk premium into factor covariances and factor risk prices as in Equation (11). In the model, factor risk prices are exogenously specified in the pricing kernel. Panels E and F report the covariances with the aggregate productivity shock and the technology frontier shock as functions of the detrended capital. Interestingly, the covariance with the aggregate productivity shock is flat, independent of the cross sectional capital age. This happens because both v_t and d_t in Equation (14) 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 Δx_{t+1}. Thus, the covariances with the aggregate productivity shock Δx_{t+1} across all firms with different capital age are equal to a constant. That is, the exposure to the aggregate productivity shock does not drive the cross sectional stock return.

In Panel F, the covariance with the technology frontier shock is decreasing in capital. Comparing with Panels B and C, the intuition behind the model is clear. As the capital of a non-adopting firm depreciates over time, both its capital age and adoption probability increase and hence its exposure (measured by the covariance) to the technology frontier shock increases. Therefore, its risk premium also increases with the risk price of the frontier shock being positive. This mechanism also allows the model to generate a failure of the standard capital asset pricing model (CAPM) in capturing the cross sectional risk premia because the aggregate productivity shock only drives the market return.

4.3 Cross sectional stock returns

An important characteristic that distinguishes the model from the standard investment-based models is capital age. The technology frontier represents the latest technology embodied in the newest capital, which is defined as age zero. Firms that are close to the technology frontier have a young capital age; in contrast, firms that are far from the technology frontier operate with old capital. Our model predicts that old capital firms are riskier and earn higher expected returns than young capital firms. In this section, we perform asset pricing tests using the model–generated data to quantitatively explore the relationship between capital age and stock returns in the cross section.

4.3.1 Capital age sorted portfolios

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

We create ten value- and equal-weighted 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 shows 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 9.6% and 15.2% per annum for value- and equal-weighted portfolios, respectively[10].

We then test the standard capital asset pricing model (CAPM) using the ten value- and equal-weighted capital age portfolios 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,

$$R^e_{j,t} = \alpha_j + \beta_{j,M}\text{Mkt}_t + \epsilon_{j,t}, \tag{16}$$

where $R^e_{j,t}$ denotes the portfolio excess return, $\beta_{j,M}$ measures the quantity of the market risk,

[10]Because firms are all-equity financed in the model, but use both debt and equity in the real data, we leverage up all returns generated in the model to make them comparable with the data. We compute the model-implied levered return as $r^e_{t+1} = (1 + \text{Debt/Equity}) \times (R^a_t - R_f)$, where R^a is the return of the all-equity firm in the model and R_f is the risk-free rate. We set the debt-to-equity ratio equal to 0.67, which is the average value of book value of debt over market value of equity for U.S. publicly listed firms.

and α_j denotes the abnormal return. The results reported in Panel C of Table 3 show that the market risk does not explain the cross sectional returns of the capital age portfolios. In the model, the annual abnormal returns of the value- and equal-weighted OMY portfolio are about 10% and 15.4%, respectively, close to the raw return spreads without adjusting the market risk. The CAPM fails in explaining the cross-sectional variations of the capital age portfolio returns.

Then we investigate a two-factor model where the market excess return is the first factor and the technology frontier shock is the second. Specifically, we use the following stochastic discount factor (investors' marginal utility):

$$M_t = 1 - b_M \times \text{Mkt}_t - b_\eta \times \text{Frontier}_t, \tag{17}$$

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 Frontier, which is the technology frontier shock ($\Delta \log N_{t+1}$). Note that the specification of the stochastic discount factor in Equation (8) is closely related to that in the model given in Equation (17) because the market factor is used here as a proxy for the aggregate productivity shock[11]. We then estimate the risk factor loadings on the two aggregate shocks (b_M and b_η) 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:

$$E\left[r_{it}^e\right] = \alpha_i + b_M \text{Cov}(\text{Mkt}_t, r_{it}^e) + b_\eta \text{Cov}(\text{Frontier}_t, r_{it}^e), \tag{18}$$

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

Panel B in Table 3 reports the multivariate covariances implied by the two-factor model, while Panel C reports the estimated alphas. Through this decomposition, we find that

[11] We include market excess return as a factor because this allows us to compare the two factor model results with the CAPM. Furthermore, in the model, across panels, a multivariate time-series regression of the aggregate stock market return on the two risk factors has an average regression R^2 of 95%, a univariate regression on the aggregate productivity shock has an average regression R^2 of 95%, but a univariate regression on the technological frontier shock has an average regression R^2 of almost zero (results not tabulated).

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 frontier risk, the exposures to the technology frontier shock across the capital age portfolio explain the cross sectional expected returns. Specifically, the covariance of the spread OMY portfolio with the technology frontier shock is 2.0 and 3.2 for the value- and equal-weighted portfolios, respectively.

Figure 2 plots the covariances of 10 value-weighted capital age-sorted portfolio returns with the aggregate productivity shock and the technology frontier shock in the simulated data. Even though old (10) and young capital age (1) portfolios have the same exposure to aggregate productivity, they significantly differ in their exposure to the technology frontier risk. This is the channel that generates the cross-sectional dispersion in average returns across the capital age portfolios.

4.4 Inspecting the mechanism

In this section we perform several analyses to understand the economic mechanism driving the cross-sectional variation of the capital age portfolios. We examine 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 (Specification 2). We find that a positive λ_η is necessary for the model to generate cross sectional risk premia. In this specification, even though the technology frontier shock affects firms' cash flows, it does not affect the marginal utility of investors and hence it is not a priced risk. As a result, the risk exposure to this shock is not associated with any risk premium. This explains why the OMY portfolio has a spread of almost zero (for both the return and CAPM alpha spreads) even though the spread portfolio's covariance with the technology frontier is 1.63 (not tabulated), a value close to the one in the benchmark case (1.96). Note that setting $\lambda_\eta = 0$ does affect the real quantities in the model. The average capital age is 27 quarters, bigger than the benchmark calibration (Specification 1). This is because the market return is higher with $\lambda_\eta = 0$ resulting in higher cost of equity, thus firms on average adopt new technologies less frequently.

The role of adoption costs. The presence of a fixed technology adoption cost is key to match both firms' capital age dynamics and the cross sectional risk premia. In Specification 3, we set $f_a = 0$, i.e., there is no fixed adoption cost. The average capital age drops from 20 quarters in the benchmark calibration to 3 quarters. This happens because all firms that are willing to adopt the latest capital will be able to reach the technology frontier, resulting in a lower average capital age in the economy. Moreover, without fixed adoption costs, firms burdened with old capital can now upgrade to the frontier technology freely. As a result, the cross sectional risk dispersion between young and old capital firms drops substantially; the capital age spread is almost 0%.

The role of operating costs. Turning off the fixed operating cost slightly increases the mean capital age (23 vs 20 in the benchmark) because of a higher average cost of equity. It is also worth noting that the model implied capital age spread remain sizable at 8.37%. This is because the cross sectional variation of the capital age portfolio is mainly driven by firms' exposure to the technology frontier shock. However, the fixed operating cost has an impact on the model's ability to generate a sizable value premium, because it affects firms' cash flows through the operating leverage channel (more on this effect in Section 4.4.1 below).

The role of technology frontier risk. In the last specification, we explore the role of technology frontier risk for asset returns. In particular, we make this risk negligible, i.e., lowering σ_N to 10% of the benchmark value, 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, because the cross-sectional variation of firms' exposure to the frontier shock shrinks to almost zero.

To summarize, we find that costly technology adoption combined with a positively priced and sizable technology frontier shock are important for the model to generate the cross sectional variation of stock returns close to the data.

4.4.1 Value premium

In addition to generating risk dispersion between young and old capital age firms, the model also provides a novel explanation for the value premium, which we explore in this section. Specifically, we form ten value-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 market value of equity. The portfolios are rebalanced at a quarterly frequency and the reported returns are annualized.

The model generates a sizable value premium at 6.1% per annum, close to the data counterpart of 8.7%, reported in Table 4. In addition, the model implied CAPM alpha spread is 6% per annum, close to the data as well. In the model, value firms have experienced a sequence of low productivity shocks that, given the presence of adoption costs, has prevented them from upgrading to the technology frontier. As a result, they are burdened with old capital. Conversely, growth firms have experienced a sequence of high productivity shocks that allows them to take on the adoption costs to replace the old capital. As a result, growth firms are operating with the latest technology. Thus, value firms in the model have higher capital age and are more exposed to the technology frontier shocks than growth firms which are low capital age firms. This can be seen in Specification 3 in Table 4 where we remove the adoption cost, which causes the value premium to become negative. Another equally important channel for the sizable value premium is the operating leverage channel. Removing the fixed operating costs (Specification 4 in Table 4) also results in a tiny value premium. This happens because value firms in the model are also the firms that have higher fixed operating costs relative to sales than growth firms. Taken together, the model implied value premium is driven by both the technology adoption costs and the operating costs, whereas the capital age spread is mainly driven by the costly technology adoption channel.

5 Measuring capital age

As discussed in the related literature, the firm's capital age is not directly observable. Because there is no readily available data, we follow the empirical industrial organization literature to measure capital age of U.S. public companies. This measurement exercise is key for our analysis, because it allows us to link firms' capital age to the cross-sectional returns in the data and test the models' predictions.

5.1 Data

Monthly stock returns are from the Center for Research in Security Prices (CRSP) for the period of October 1976 to December 2016 and accounting information is from the CRSP/Compustat Merged Quarterly Industrial Files for the period of 1975q1 to 2016q4. The sample 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) or greater than 9000 (government/administrative institutions). We also exclude R&D–intensive sectors (SIC codes 737, 384, 382, 367, 366, 357, and 283) from our sample,[12] because our theoretical model applies to firms that upgrade the technology through investing in the latest machines and equipment which embody the frontier technology (exogenous in our model). Our setup is not necessarily suitable to study 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)).

5.2 Capital age

Dunne (1994) shows that technology embodied in new capital (i.e., capital age) and the firm's age (i.e., years from IPO or years from incorporation) display little comovement [13]. For this reason, we measure capital age following methodologies developed in the empirical industrial organization literature (e.g., Salvanes and Tveteras (2004)).

We include a firm in our dataset the first time it has observations on net property plant and equipment (Compustat item *ppentq*) for two consecutive quarters, which we identify as quarter 0 and quarter 1. The initial measure of real capital stock ($K_{i,0}$) is firm i's net property plant and equipment deflated using the seasonally adjusted implicit price deflator for non–residential fixed investment. The initial measure of firm–level capital age ($AGE_{i,0}$) is calculated using the ratio of accumulated depreciation and amortization (item *dpactq*) over current depreciation and amortization (item *dpq*)[14].

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

[13] Our analysis confirms Dunne (1994)'s findings. The correlation between our measure of capital age and firm's age measured as time from IPO is only 0.30.

[14] 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

We calculate the net investment $I^N_{i,t}$ and gross investment $I_{i,t}$ of firm i between period t and $t+1$ as

$$\begin{aligned} I^N_{i,t} &= K_{i,t+1} - K_{i,t}, & (19) \\ I_{i,t} &= \delta_j K_{i,t} + I^N_{i,t}, & (20) \end{aligned}$$

respectively. In the above equation, δ_j denotes the depreciation rate of industry j calculated using depreciation data from the BEA.[15]

Given a time–series of real capital stock and gross investment observations for a firm, we solve for the capital age of firm i over time recursively starting from its initial capital age $AGE_{i,0}$ using equations:

$$AGE_{i,t} = \begin{cases} \frac{(1-\delta_j)K_{i,t-1}}{K_{i,t}}(AGE_{i,t-1}+1) + \frac{I_{i,t-1}}{K_{i,t}} & \text{if} \quad I_{i,t-1} > 0, \\ AGE_{i,t-1}+1 & \text{if} \quad I_{i,t-1} \leq 0. \end{cases} \tag{21}$$

When gross investment $I_{i,t-1}$ is positive at quarter t, the investment at $t-1$ has a capital age of 1 quarter and the capital installed at $t-1$ has a capital age of $AGE_{i,t-1}+1$ quarters. The capital age at t is defined as the weighted average of the two where weights are the real capital stock at $t-1$ after depreciation scaled by the real capital stock at t $\left(\frac{(1-\delta_j)K_{i,t-1}}{K_{i,t}}\right)$ and real gross investment scaled by the real capital stock at t $\left(\frac{I_{i,t-1}}{K_{i,t}}\right)$.[16] Note that the sum of the two weights equals to 1 because $K_{i,t} = (1-\delta_j)K_{i,t-1} + I_{i,t-1}$. When gross investment $I_{i,t-1}$ is negative, we assume that firms dispose of all capital vintages in proportion to their contribution to the total installed capital. Hence, the capital age increases by one quarter.[17]

and amortization (*dpactq*) in a given fiscal quarter is missing, we use the end of the fiscal year value. When 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. If *dpq* is missing, we set it equal to the industry depreciation rate times physical capital (*ppentq*).

[15]We calculate industry-level (3-digit SIC codes) depreciation rates using depreciation and capital stock data for private fixed asset from the BEA. If a company has only a 2-digit (1-digit) SIC code, we use the average depreciation rate at the 2-digit (1-digit) level. For companies without a SIC code, we set the depreciation rate equal to the unconditional average value calculated using firm-level observations for which the depreciation rate is available.

[16]If real capital stock is missing for one quarter, we linearly interpolate the real capital stock from two nearby quarters to compute the capital age. If real capital stock is missing for two consecutive quarters, we drop the rest of the observations for a firm.

[17]Given the lack of information about the capital age of acquired assets, we assume that the capital age

Quarterly coverage of net property plant and equipment in Compustat becomes systematic starting in the period 1975/1976.[18] For this reason, we construct capital age starting from the first quarter of 1975. However, our portfolio formation starts using accounting data from the first quarter of 1976 to allow for a sufficiently large number of observations in each portfolio.

5.3 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. We include in our dataset only firms that have all of the above available in a given quarter. In total, our sample consists of 311,717 firm–quarter observations. All the quantities are winsorized at the top and bottom 1 percent to attenuate the impact of outliers.

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 22.6 (20.7) quarters with a volatility of 12.5 quarters.[19] Quarterly firm-level investment rate is 5.4% with a volatility of 14.7%. The average firms' return on equity and book-to-market ratio are 0.5% and 0.83, respectively, with respective volatilities of 11% and 0.7, consistent with the range of empirical estimates in the literature. The average log size of the firms in the sample is 5 when we measure size in 2009 (million) dollar term.

A natural concern for the measure of capital age is whether the capital age merely captures the (inverse) investment effect (i.e., 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 -0.24, suggesting that capital age and investment contain different information. Furthermore, capital age is also only weakly correlated with book-to-market, return-on-equity and log size with correlations of 0.19, 0.10 and 0.12, respectively.

increases by one quarter when there is an acquisition larger than 50% of the beginning of the quarter capital stock. This assumption has no material effect on our empirical analysis.

[18]For the fiscal year 1974, only 11% of firms report *ppentq* for fiscal quarters other that the last one. This percentage increases to 50% in the fiscal year 1975 and to 93% in the fiscal year 1976.

[19]Ai, Croce, and Li (2013) also calculate a firm's capital age using data on investment expenditures and find a median value of five years.

5.4 Alternative measure of capital age

We also consider an alternative (albeit related) measure of capital age to show the robustness of our main measure. 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 (21).

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 (labelled as Capital Age Alt) has a mean of 20 quarters with a volatility of 11 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 94%, 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 -0.20, 0.13, and 0.18, respectively. We report the results from several robustness checks using this alternative measure of capital age in Appendix A4.

6 Empirical analysis

In this section, we provide evidence on the relation between capital age and the cross–section of stock 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. We also investigate the joint link between capital age and other firm-level characteristics on one hand and future stock returns on the other using multivariate regression techniques. Lastly, we construct a proxy for the aggregate technology frontier shock, which we show is a positively priced source of aggregate risk and that old capital age firms are more exposed to this shock than young capital age firms, corroborating the model mechanism.

6.1 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 to avoid a look-ahead bias. 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 $t+1$. The first portfolio is formed in October 1976, the last one in October 2016.

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 ($E[R^e]$, 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, on average, subsequently lower returns than firms with currently high capital age. The difference in returns is economically large and statistically significant. The average equal-weighted return spread (OMY, the capital age return spread) is 14.9% per annum, and this value is more than 5.9 standard errors away from zero. The average value-weighted capital age return spread is 9.5% per annum, and this value is 2.4 standard errors away 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. Lastly, we also highlight the fact that the Sharpe ratio across capital age portfolios is also increasing in firms' current capital age, a finding consistent with the model's prediction.

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

Previous studies document a negative relation between the firm's investment rate and future stock returns in the cross section. As reported in Table 5, the capital age and investment rate 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 behavior of 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 age. 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 OMY) 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 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 8.6% to 11.4% 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 around 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 of 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.

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 spreads are positive across all book-to-market bins and significant for the middle book-to-market bin.

6.3 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 and French (2015) five-factor model (FF5). This analysis is important because it provides information about the class of models that can potentially explain the capital age spread[20].

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). The intercepts from these regressions are the pricing errors (abnormal returns)

Panels B and C of Table 6 report the alphas (i.e., the pricing errors) and betas for the CAPM and the Fama-French five-factor model 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 5.1% per annum using equal-weighted returns and 3.3% per annum in value-weighted returns. The

[20]The results using the Hou, Xue, and Zhang (2015) four-factor model (HXZ) are reported in Section A4.2 in the Appendix.

alpha of the capital age spread portfolio is large and significant, between 18% per annum for equal-weighted returns and 15% 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 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 does a better job here than the CAPM for both equal- and value-weighted returns. The mean absolute pricing error of the Fama-French model drops significantly relative to the one implied by the CAPM (2.0% vs 5.1% for equal-weighted returns, 2.2% vs 3.3% for 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 average abnormal return (alpha) of the capital age return spread portfolio is 9.4% and 6.3% per annum, respectively in equal- and value-weighted returns, and these values are 4.2 and 2.8 standard errors from zero. In untabulated results, we also include the liquidity factor of Pastor and Stambaugh (2003) on top of FF5 to control for liquidity–related issues and the results are virtually unchanged[21].

The asset pricing tests for the nine portfolios two-way-sorted on capital age on one hand and investment rate, size, 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 excess returns (OMY) across the two factor models are always positive and significant for the equal-weighted portfolios. 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 FF5 has an investment–based factor that seems to pick up some of the variability in capital age sorted portfolios only when we double sort using the investment rate. Overall, the results in Table 8 show that the capital age spread alpha remains positive

[21] The Fama and French factors 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.

and significantly different from zero at the 5% level in most of the cases.

Taken together, the Fama-French five-factor model captures a larger fraction of the cross-sectional variation in the average returns of the capital age portfolios than the CAPM, but this factor model cannot fully explain the variation of the one-way sorted capital age spread. Not surprisingly, the capital age spread is partially subsumed when we two-way sort on both capital age and investment rate, which is an important determinant of capital age. In the next section, we go beyond two-way-sorted portfolios and control for multiple characteristics simultaneously by running cross–sectional regressions.

6.4 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 Fama and MacBeth (1973) firm-level cross-sectional 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[22]. This regression allows for a clear economic interpretation of the regression slopes and further validation of 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.

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

[22]The results using pooled ordinary least squares (OLS) regressions are reported in Section A4.2 in the Appendix.

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 0.40, which is more than 6 standard deviations from zero. It implies that that a one standard deviation increase in (log) capital age leads to a significant increase of 0.40% in the average monthly equity return. The difference in average (log) capital age between firms in the top and bottom decile is equivalent to 3.5 standard deviations. The coefficient in Column 1 implies a difference in expected returns of 1.4% per month, which is equivalent to an annualized difference of 16.8%, a value close to 15.0%, the equally–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 0.26 (specification 6) to 0.42 (in specification 2), 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 35% smaller than the value in specification 1. In this case, a one standard deviation increase in capital age leads to a significant increase of 0.26% in the average monthly equity return, which translates in an annualized return of 3.1%.

6.5 The capital age spread and technology frontier shocks

In the previous sections, we show that the capital age spread is not captured by the standard factor models. In this section, we provide empirical evidence for the link between the capital age spread and a proxy for the aggregate technology frontier shock which drives firms' technology adoptions, corroborating the model predictions.

Specifically, we follow Baron and Schmidt (2017) and use the introduction of technology standards to capture the adoption of new technologies.[23] The key macroeconomic variable that we use is the aggregate 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

[23] More information can be found at http://www.law.northwestern.edu/research-faculty/searlecenter/innovationeconomics/data/technologystandards/.

classification of standards (ICS) class 33) and Information Technology and Office Machines (ICS class 35). Consistent with the view in Baron and Schmidt (2017), who show that the introduction of new technology standards anticipates the adoption of new technologies and positively correlates with future productivity gains, we take the log difference (i.e., the growth rate) in the number of new technology standards to proxy for the aggregate technology frontier shock.[24]

We show that this technology frontier shock proxy is a source of systematic risk and that the exposures to this shock capture the cross-sectional variation of the capital age portfolios. In analogy to the model, we do so by considering a two-factor asset pricing model with the stock market factor (Mkt) and the technology frontier shock proxy (Frontier) as the two factors. Specifically, we use the following stochastic discount factor (investors' marginal utility):

$$M_t = 1 - b_M \times \text{Mkt}_t - b_F \times \text{Frontier}_t, \tag{22}$$

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 Frontier, the technology frontier shock. Note that the specification of the stochastic discount factor in Equation (22) is closely related to that in the model given in Equation (17). We then estimate the risk factor loadings on the two aggregate shocks (b_M and b_F) 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:

$$E\left[r_{it}^e\right] = \alpha_i + b_M \text{Cov}(\text{Mkt}_t, r_{it}^e) + b_F \text{Cov}(\text{Frontier}_t, r_{it}^e), \tag{23}$$

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

We first examine the pricing result across the 10 value-weighted capital age portfolios. In Panel A of Table 10 we report the alphas (pricing errors) for the 10 age portfolios and the spread portfolio (OMY) implied by the two-factor model in Equation (23) (Specification

[24] 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.

1). We also calculate the multivariate covariances between the capital age portfolio excess returns and the Frontier shock. We find that the two-factor model produces a small and insignificant pricing error for the capital age spread (OMY) at 2.4% per annum with the t-stat at 1. In addition, the covariances between the Frontier shock and the capital age spread is 2.2 with the t-stat at 2.3, implying that the frontier shock proxy generates significant variation for the risk exposure across the capital age portfolios.

Furthermore, we investigate the extent to which the technology frontier shock proxy captures information about systematic risk in the economy not captured by other macroeconomic variables used in the literature, some of which have already been shown to be correlated with asset prices in the cross section. As such, in addition to the Frontier shock, we also test the pricing properties of the 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, Lettau and Ludvigson (2001)) , the Pastor and Stambaugh (2003) aggregate liquidity shock, the log change in the BAA-AAA spread, the change in macroecomonic uncertainty (Jurado, Ludvigson, and Ng (2013)), and a proxy for investment-specific technology shocks based on the relative price of capital goods (Papanikolaou (2011))[25]. All the data are at a quarterly frequency over the period that goes from the fourth quarter of 1976 to the fourth quarter of 2014. To facilitate the comparison, all the macroeconomic factors are demeaned and divided by their unconditional standard deviations.[26]

Panel A (Specifications 2 to 8) reports the pricing errors and the multivariate covariances between the capital age portfolio excess returns and each macroeconomic shock implied by

[25]We also use the proxy for investment-specific technology shocks based on return spreads between investment and consumption sectors (IMC) introduced by Papanikolaou (2011) and obtain similar results.

[26]The data for real GDP and for the BAA and AAA corporate bond yields are from the Federal Reserve Economic Database (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 (2015). 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. The data on quarterly investment-specific technology shocks are from Garlappi and Song (2016). Different from the other data, the latter quantity is available only until the last quarter of 2012.

the two-factor model with the market factor and one macroeconomic shock (replacing the Frontier shock) one at a time. The alphas (pricing errors) implied by the two factor model with the macroeconomic shocks are much larger than that of the Frontier shock, ranging from 9% to 17%. Moreover, the two factor models with these macroeconomic shocks, with the exception of the log change in real GDP, fail to generate a significantly different risk exposure between the old capital age and young capital age portfolios.

In Panel B, we report the result of the one-step GMM estimation of the SDF in Equation (22). Not surprisingly, the one-factor model based on the market excess returns (Specification 1) produces a large pricing error with an mean absolute error (m.a.e.) of 3.4% per annum. Adding the technology frontier shock proxy as a second factor (Specification 2) significantly decreases the m.a.e. to 1.8%. To examine the marginal effect of the technology frontier shock proxy for asset prices, we also estimate a three factor model with the market excess return (Mkt), the technology frontier shock proxy (Frontier), and one macroeconomic shock (Macro) at a time as follows

$$M_t = 1 - b_M \times \text{Mkt}_t - b_F \times \text{Frontier}_t - b_{Macro} \times \text{Macro}_t. \tag{24}$$

Panel B (Specifications 3 to 9) shows that the risk factor loading on the Frontier shock always remains significant and its estimated value does not change dramatically across the different specifications. It is worth noting that only *cay* is marginally significant among these macro factors when we also include the technology frontier shock.

At the bottom of Panel B, we also report a rank test for individual factors as suggested by Gospodinov, Kan, and Robotti (2014). In particular, we test if the matrix $E[x_t(1, f_t)]$ has a column rank of one (i.e., full rank), where x_t is the matrix of test assets' returns and f_t is a risk factor. This test allows us to verify if the technology frontier shock proxy is indeed a useful factor (i.e., its significance is not driven by the fact that this risk factor is independent of the test asset returns). As we can see, the corresponding p-value is less than 0.05, so we can reject the null hypothesis that $E[x_t(1, f_t)]$ has less than full rank and conclude that the technology frontier shock proxy is correlated with the assets returns.

Panels A and Panel B validate our model's prediction that capital age predicts expected returns because it entails an exposure to the technology frontier shock proxy, which is a source of systematic risk. In Panel C of Table 10, we further explore if this source of risk is also priced in a broader set of test assets. To this end, we follow Lewellen, Nagel and Shanken (2010) by including the 17 Fama-French industry portfolios as test assets. In addition, we also include the 6 size and book-to-market portfolios and the 10 momentum portfolios, as in Gospodinov, Kan, and Robotti (2014). We test the same factor models as in Panel B and find consistent results. The risk factor loading on the technology frontier shock proxy is statistically significant in the two-factor model ($t\text{-}stat = 2.7$) and is always significant in the various three-factor model specifications.[27] Taken together, the technology frontier shock proxy captures a source of systematic risk that is priced in the economy, consistent with the model's implications.

7 Conclusion

We study how the time–variation of the aggregate technological frontier impacts firms' asset prices and real quantities in a dynamic model economy. Our results show that costly technology adoption combined with a systematic technology frontier shock are important in shaping the cross section of stock returns. In our setting, technology adopting firms are less risky than non-adopting firms because costly technology adoption limits the flexibilities of non-adopting firms in upgrading their old capital to the frontier, causing their continuation value to be more exposed to the frontier 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.

Furthermore, we provide empirical evidence for the model's predictions. In particular, we construct a measure of firms' capital age and find an annual value-weighted return spread of 9% between old and young capital firms; in addition, the standard asset pricing factor models fail to explain the variation of the capital age return spread. Furthermore, we estimate a proxy for the technology frontier shock by using the introduction of technology standards in the US and worldwide. We show this aggregate technology frontier shock proxy captures the cross-sectional variations of the capital age portfolios.

Our work has implications for both macroeconomics and finance. Our findings suggest that technology adoptions can have a significant impact on asset prices. In addition, our analysis shows that risk premiums are an important determinant of firms' adoption decisions.

[27]Note that only the TFP shock remains significant when we include the technology frontier shock.

Given the importance of technological changes in economic growth and business cycles, our results suggest that incorporating cross-sectional variation in risk premiums in current DSGE models can be important for an accurate understanding of technology adoption over the business cycle and of how technology adoption frictions propagate and amplify the effect of shocks in the economy.

References

Abel, A. B. and J. E. Eberly, 2012, Investment, Valuation, and Growth Options, *Quarterly Journal of Finance*, 2(1)

Ai, H., M. M. Croce, and K. Li, 2013, Toward a Quantitative General Equilibrium Asset Pricing Model with Intangible Capital, *Review of Financial Studies*, 26 (2): 491–530

Ai, H., M. M. Croce, A. Diercks, and K. Li, 2017, News Shocks and Production-Based Term Structure of Equity Returns, Review of Financial Studies, forthcoming

Albuquerque, R. and N. Wang, 2008, Agency Conflicts, Investment and Asset Pricing, *Journal of Finance*, 63(1): 1-40.

Baron, J. and J. Schmidt, 2017, Technological Standardization, Endogenous Productivity and Transitory Dynamics, Banque de France Working Paper No. 503

Brown, J., S. M. Fazzari, and B. C. Petersen 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance* 54(1): 151

Brown, J. R. and B. C. Petersen 2011. Cash holdings and r&d smoothing. *Journal of Corporate Finance* 17: 694-709

Cooper, R., J. Haltiwanger and L. Power, 1999, Machine Replacement and the Business Cycles: Lumps and Bumps, *The American Economic Review*, 89 4, 921-946.

Cummins, J. and G. L. Violante. 2002. Investment-Specific Technological Change in the U.S. (1947-2000): Measurement and Macroeconomic Consequences, *Review of Economic Dynamics*, vol. 5(2), April 2002, pages 243-284.

Dunne, T. 1994. Plant Age and Technology use in U.S. Manufacturing Industries. *The RAND Journal of Economics* 25(3): 488-499

Eisfeldt, A., and D. Papanikolaou, 2013. Organization Capital and the Cross-Section of Expected Returns. *Journal of Finance* 68(4): 1365-1406

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* $116(1), 1-22$

Fama, E. and J. D. MacBeth 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81(3), 607-636.

Garlappi, L., and Song, Z., 2016, Can Investment Shocks Explain the Cross Section of Equity Returns?, *Management Science* $63, 3829-3848$

Garleanu, N., Panageas, S, and J. Yu, 2012, Technological growth and asset Pricing, *Journal of Finance* $67, 1265-1292$

Gordon, R. J. 1990, The Measurement of Durable Good Prices, NBER Monograph Series, University of Chicago press.

Gospodinov, N., R. Kan, and C. Robotti, 2014, Misspecification-Robust Inference in Linear Asset-Pricing Models with Irrelevant Risk Factors, *Review of Financial Studies* $27(7), 2139-2170$

Greenwood, J., Z. Hercowitz, and P. Krusell. 1997. Long-run implications of investment-specific technological change. *American Economic Review* 87 (3): 342–362.

Greenwood, J., and M. Yorukoglu, 1997, Carnegie-Rochester Conference Series on Public Policy 46: 49-95, Elsevier Science

Hou, K., Xue, C., and L. Zhang, 2015, Digesting Anomalies: An Investment Approach, *Review of Financial Studies* $28(3), 650-705$

Hulten, C. R. 1991. The measurement of capital. Fifty years of economic measurement. In: Berndt, E.R., Triplett, J.E. (Eds.), Studies in Income and Wealth. The National Bureau of Economic Research, Chicago, pp. 119-158 (The University of Chicago Press 54 (June)).

Imrohoroglu, A., and S. Tuzel, 2014, Firm level productivity, risk and return, *Management Science*, 60

Jermann, U., 1998. Asset pricing in production economies, *Journal of Monetary Economics*, 41, 257–275.

Jorgenson, D. W. 2001, Information Technology and the U.S. Economy, *American Economic Review*, vol. 91(1), pages 1-32.

Jovanovic, B., and D. Stolyarov. 2000. Optimal adoption of complementary technologies , *American Economic Review* 90, 15–29.

Jurado, K., S. Ludvigson, and S. Ng 2015. Measuring Uncertainty, *American Economic Review* 105(3), 1177–1215.

Kogan, L., and D. Papanikolaou. 2014 "Growth opportunities, technology shocks, and asset prices." *Journal of Finance* , 69, 675-718.

Kung, H. and L. Schmid 2015. Innovation, Growth, and Asset Prices. *Journal of Finance* 70(3), 1001.

Lettau, M. and S. C. Ludvigson 2001. Consumption, Aggregate Wealth, and Expected Stock Returns. *Journal of Finance* 56(3), 815

Lewellen, J., S. Nagel, and J. Shanken, 2010, A Skeptical Appraisal of Asset Pricing Tests, *Journal of Financial Economics*, 96 (2), 174-194

Liao, W. and L. Schmid 2017. Levered Ideas: Risk Premia along the Credit Cycle. Duke University Working Paper.

Lustig, H., C. Syverson, and S. V. Nieuwerburgh 2011. Technological Change and the Growing Inequality in Managerial Compensation. *Journal of Financial Economics* 99(3), 601-627.

Mairesse, J., 1978, New Estimates of Embodied and Disembodied Technical Progress, *Annales de l' Insee*, 30/31: 681-720

Papanikolaou, D. 2011 "Investment Shocks and Asset Prices." *Journal of Political Economy* , 119(4), 639-685.

Parente S. L., and E. C. Prescott, 1994, Barriers to technology adoption and development, *Journal of Political Economy* 102 (2): 298-321

Pastor, L. and P. Veronesi, 2009. Technological revolutions and stock prices. *American Economic Review* 99, 1451-1483.

Pastor, L. and R. F. Stambaugh, 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111(3), 642-685.

Rich, J., Jones, J., Mowen, M., and D. Hansen. 2014. Cornerstones of Financial Accounting, South-Western. Cengage Learning; 3rd edition

Rouwenhorst, G. 1995. Asset pricing implications of equilibrium business cycle models, in Thomas Cooley, eds. *Frontiers of Business Cycle Research.* Princeton NJ: Princeton University Press.

Salvanes, K. J., and R. Tveteras. 2004. Planx exit, vintage capital, and the business cycle. *Journal of Industrial Organization* 52 (2): 255-276.

Zhang, L., 2005. The value premium. *Journal of Finance* 60 (1), 67–103

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

$$v_t = \frac{V_t}{X_t N_t} \quad (25)$$

$$k_t = \frac{K_t}{N_t} \quad (26)$$

$$d_t = \frac{D_t}{X_t N_t}. \quad (27)$$

After some algebra, the firm problem is equivalent to

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

where

$$d_t = e^{z_t} k_t - [f_a k_t + i_t k_t] \phi_t - f_o \quad (28)$$

$$G = -r + g_x + \frac{1}{2}\sigma_x^2 - \sigma_x \lambda_e. \quad (29)$$

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

$$k_{t+1} = \begin{cases} (1-\delta) k_t e^{-g_N - \sigma_N \eta_t} & \text{if} \quad \phi_t = 0 \\ 1 & \text{if} \quad \phi_t = 1 \end{cases} \quad (30)$$

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

$$i_t = \begin{cases} 0 & \text{if} \quad \phi_t = 0 \\ \frac{1}{k_t} e^{g_N + \sigma_N \eta_t} - 1 + \delta & \text{if} \quad \phi_t = 1 \end{cases} \tag{31}$$

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 adoption (ϕ_t) 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 $1,000$ 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 7 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 ($\delta_j K_{i,t} + I_{i,t}^N$) 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

A4.1 Alternative Measure of Capital Age

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.

A4.2 Additional Results

In this section we report (i) the risk–adjusted excess returns across single-sorted and double-sorted portfolios using the Hou, Xue, and Zhang (2015) four-factor model and (ii) the results from pooled OLS predictability regressions.

To produce risk-adjusted returns using the Hou-Xue-Zhang four-factor model, we augment the CAPM regressions with their size factor (ME), investment factor (IA) and profitability factor (ROE). Table A3 shows that the mean absolute pricing error of the Hou-Xue-Zhang model across age–sorted portfolios is also significantly smaller than the CAPM one (2.6% versus 5.1% for equal-weighted returns, 1.6% versus 3.3% for value-weighted returns). The average abnormal return (alpha) of the capital age return spread portfolio implied by the Hou-Xue-Zhang model is 7.3% and 5.4% per annum, respectively in equal- and value-weighted returns, and these values are 2.6 and 2.1 standard errors from zero. Table A4 reports the pricing errors across double–sorted portfolios. Overall, the results are very similar to the ones produced using the Fama and French (2015) five-factor model.

Table A5 reports the results from pooled OLS predictability regressions. The estimation here is performed at a quarterly frequency, and includes firm and quarter fixed effects. The capital age slope coefficients are positive and significant in all specifications. The estimated values range from 0.17 (specification 6) to 0.64 (specifications 1 and 5) and they are all more than 3 standard errors away from zero.

Table 1: Parameter values under benchmark calibration

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

Parameter	Value	Description
Stochastic Process		
$4g_N$	0.02	Average log growth of aggregate technology frontier
σ_N	0.0775	Volatility of log growth of aggregate technology frontier
$4g_x$	0.012	Average log growth of aggregate productivity
σ_x	0.047	Volatility of log growth of aggregate productivity
ρ_z	0.97^3	Persistence of firm-specific productivity
$\bar{z}$	-1.73	Long run average of firm-specific productivity
σ_z	0.18	Conditional volatility of firm-specific productivity
Technology		
δ	0.025	Rate of capital depreciation
f_a	3.4	Fixed cost of technology adoption
f_o	0.06	Fixed operating cost
Pricing kernel		
$4r$	0.022	The real risk-free rate
λ_e/σ_x	5	Risk price of aggregate productivity shock
λ_η/σ_N	5	Risk price of aggregate technology frontier shock

Table 2: Unconditional moments under the benchmark calibration

This table presents the selected moments in the data and the corresponding ones implied by the model under the benchmark calibration. The reported statistics in the model are averages from 100 simulated samples, each with 5,000 firms and 120 quarterly observations. We report the cross-simulation averaged annual moments. The data moments are estimated from a sample from 1976 to 2016.

Moments	Data	Model
Asset prices		
Real risk-free rate (%)	2.2	2.2
Market premium (%)	5.7	5.8
Market Sharpe ratio	0.35	0.36
Average individual stock volatility (%)	48.5	42.6
Value premium (%)	8.7	6.1
Real quantities		
Std. dev. of aggregate profits (%)	14	13
Mean capital age (in quarters)	23	20
Std. dev. of capital age (in quarters)	12	14
Cross sectional correlation between capital age and BM	0.19	0.16
Cross sectional correlation between capital age and investment rate	-0.24	-0.22

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 and ten equal-weighted portfolios sorted on capital age. Panel A reports average excess returns and Sharpe ratios 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 the risk factor covariances. Panel C reports the average abnormal returns (alphas) implied by the CAPM together with the average abnormal returns (alphas) implied by a two factor model where the two factors are the market excess return (Mkt) and the technology frontier shock (Frontier). 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. Each portfolio is rebalanced at quarterly frequency. All estimates of returns are annualized.

	Value Weighted						Equal Weighted					
	Y	3	5	7	O	OMY	Y	2	5	9	O	OMY
Panel A: Portfolio Returns and Sharpe Ratios												
E[R^e]	0.81	2.55	6.70	10.42	10.41	9.60	0.92	2.68	7.26	12.69	16.10	15.18
[t]	0.23	0.78	1.97	2.98	3.15	3.60	0.29	0.85	2.12	3.30	4.14	3.83
SR	0.04	0.14	0.37	0.55	0.56	0.61	0.05	0.15	0.40	0.62	0.72	0.67
Panel B: Risk Factor Covariances												
Mkt	2.22	2.31	2.49	2.54	2.32	0.25	2.22	2.32	2.49	2.62	2.46	0.59
[t]	6.89	6.87	6.90	7.12	7.05	1.32	6.71	6.73	6.83	6.97	6.92	2.28
Frontier	-0.97	-0.69	0.12	0.98	0.90	1.96	-1.00	-0.71	0.11	1.23	2.09	3.22
[t]	-6.40	-5.91	0.70	5.64	3.51	6.02	-6.31	-5.69	0.50	5.23	5.91	6.35
Panel C: Pricing Errors: CAPM and 2 Factor Model												
Alpha	-5.82	-4.38	-0.56	3.28	4.12	9.95	-7.33	-5.93	-1.86	3.52	8.05	15.38
[t]	-2.81	-2.72	-0.63	2.11	2.05	2.92	-2.82	-2.84	-1.53	2.09	2.61	3.00
Alpha^{2F}	0.27	0.01	-0.41	-0.39	0.71	0.43	0.40	0.03	-0.31	-0.44	0.75	0.35
[t]	0.50	0.06	-0.52	-0.57	0.68	0.54	0.62	0.07	-0.39	-0.58	0.59	0.36

Table 4: Alternative model specifications

This table reports key moments generated by several alternative model specifications and their data counterpart. Model 1 is the benchmark economy. Model 2 sets the price of the technology frontier shock (λ_η) to zero. Model 3 sets $f_a = 0$, 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 10% of the benchmark value. The reported statistics for each model are averages from 100 samples of simulated data, each with 5,000 firms and 30 years of monthly observations. Each portfolio is rebalanced at quarterly frequency. All estimates of returns are annualized.

Market Risk Prem.	Market Volatility	Mean Capital Age	E[R^e] Y	E[R^e] O	E[R^e] OMY	CAPM Alpha Y	CAPM Alpha O	CAPM Alpha OMY	E[R^e] G	E[R^e] V	E[R^e] VMG	CAPM Alpha G	CAPM Alpha V	CAPM Alpha VMG
Data														
5.70	16.29	23	-0.05	9.40	9.45	-11.06	3.98	15.03	6.89	15.62	8.73	-0.54	7.52	8.06
1. Benchmark														
5.83	16.24	20.28	0.81	10.41	9.60	-5.82	4.12	9.95	3.68	9.81	6.13	-2.66	3.13	5.79
2. $\lambda_\eta = 0$														
6.71	23.73	27.03	7.05	7.24	0.19	1.77	-0.35	-2.12	6.52	6.82	0.30	-0.12	1.44	1.56
3. $f_a = 0$														
19.45	23.28	2.53	19.46	19.45	0.00	0.01	-0.01	-0.02	18.93	18.57	-0.36	-0.04	0.00	0.04
4. $f_o = 0$														
14.33	19.26	23.09	9.63	18.01	8.37	-2.21	1.72	3.93	14.52	12.56	-1.96	-0.05	-1.21	-1.16
5. $\sigma_N = 0.00775$														
6.94	16.08	24.04	7.01	6.69	-0.32	0.11	-0.24	-0.36	6.69	7.03	0.34	-0.24	0.12	0.36

Table 5: Summary Statistics

This table reports the mean, standard deviation (std), 25% percentile (p25), 50% percentile (p50), 75% percentile (p75), and number of available observations (obs) for the variables used in the empirical analysis (Panel A) and their correlations (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), government/administrative institutions (SIC codes greater than 9000), and R&D–intensive sectors (SIC codes 737, 384, 382, 367, 366, 357, and 283) from our sample. The sample period is 1976q3–2016q3. Section 5 describes the construction of the firm-level capital age measures, while Appendix A3 describes the other variables. 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	std	p25	p50	p75	obs
Capital Age	22.60	12.49	13.50	20.73	29.32	311,717
Capital Age Alt	20.20	11.49	11.93	18.33	26.01	311,717
Investment Rate	0.05	0.15	0.00	0.03	0.07	311,717
Return on Equity(%)	0.50	11.00	-0.10	2.30	4.40	311,717
Size (2009 dollars, log)	5.14	2.13	3.55	5.05	6.62	311,717
Book-to-Market	0.83	0.70	0.38	0.64	1.07	311,717

Panel B: Correlation

	Capital Age	Capital Age Alt	Investment Rate	ROE	Size (2009 $)	Book Market
Capital Age	1.00					
Capital Age Alt	0.94***	1.00				
Investment Rate	-0.24***	-0.20***	1.00			
Return on Equity	0.10***	0.13***	0.04***	1.00		
Size (2009 dollars, log)	0.12***	0.15***	0.01***	0.26***	1.00	
Book-to-Market	0.19***	0.18***	-0.14***	-0.03***	-0.35***	1.00

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

This table reports average annualized excess returns (E[R^e]), Newy-West adjusted t-statistics ([t]), and Sharpe Ratios (SR), and test results of standard asset pricing factor models (CAPM and Fama-French 5 factors) across ten value and equal weighted age-sorted portfolios in the data including the average abnormal returns (alphas) and the factor loadings (MKT, SMB, HML, RMW and CMA). Portfolios are rebalanced at a quarterly frequency starting in October 1976 and ending in October 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'.

	Value weighted						Equal weighted					
	Y	3	5	7	O	OMY	Y	3	5	7	O	OMY
Panel A: Raw returns												
	Portfolio returns and Sharpe ratios						Portfolio returns and Sharpe ratios					
E[R^e]	-0.05	6.12	5.62	8.84	9.4	9.45	-2.33	9.33	11.14	12.16	12.62	14.95
[t]	-0.01	2.04	2.09	3.72	4.28	2.39	-0.48	2.43	3.18	3.70	3.72	5.88
SR	0.00	0.32	0.33	0.58	0.67	0.45	-0.08	0.43	0.57	0.65	0.68	0.97
Panel B: CAPM												
	CAPM: MAE = 3.31						CAPM: MAE = 5.08					
Alpha	-11.06	-1.72	-1.56	2.48	3.98	15.03	-12.25	1.04	3.44	4.73	5.46	17.71
[t]	-4.38	-1.12	-1.32	1.79	2.75	4.96	-4.21	0.43	1.60	2.58	2.65	7.82
MKT	1.52	1.08	0.99	0.88	0.75	-0.77	1.37	1.14	1.06	1.02	0.99	-0.38
[t]	26.12	35.03	26.83	25.76	17.44	-9.18	20.72	21.94	21.85	19.82	15.37	-4.83
R^2	0.73	0.77	0.80	0.78	0.67	0.31	0.58	0.67	0.70	0.72	0.66	0.13
Panel C: FF5 5-factor model												
	Fama-French 5: MAE=2.22						Fama-French 5: MAE=1.98					
Alpha	-6.36	-2.63	-4.34	-1.36	-0.09	6.27	-8.50	-5.22	0.04	1.30	0.94	9.44
[t]	-2.75	-1.82	-3.90	-1.34	-0.09	2.76	-2.91	-2.25	0.03	1.06	0.69	4.25
MKT	1.26	1.02	1.05	0.98	0.90	-0.37	1.07	1.03	1.01	1.02	0.99	-0.08
[t]	24.93	33.44	38.11	42.92	43.65	-6.65	17.67	28.25	32.45	34.33	28.45	-1.62
SMB	0.50	037	0.13	0.06	-0.01	-0.51	0.93	0.92	0.85	0.77	0.80	-0.13
[t]	5.66	7.06	3.19	1.54	-0.20	-5.21	8.10	13.65	14.23	14.60	14.02	-1.65
HML	0.11	0.08	0.10	0.05	0.22	0.12	0.25	0.35	0.31	0.34	0.46	0.21
[t]	1.11	0.99	2.16	1.17	4.38	1.23	1.50	3.89	4.01	4.25	5.15	1.70
RMW	-0.25	0.26	0.40	0.53	0.23	0.48	-0.58	-0.05	0.10	0.17	0.14	0.72
[t]	-1.98	4.29	7.36	9.90	3.72	4.42	-2.99	-0.56	1.12	1.91	1.62	5.49
CMA	-1.00	-0.30	0.01	0.16	0.38	1.38	-0.74	-0.22	-0.02	0.13	0.05	0.79
[t]	-7.15	-3.24	0.09	2.56	5.18	9.29	-2.29	-1.58	-0.13	1.12	0.41	3.20
R^2	0.81	0.81	0.84	0.86	0.78	0.62	0.75	0.85	0.88	0.90	0.87	0.45

Table 7: Average Returns of Double Sorted Portfolios

This table reports average annualized excess return across 3×3 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 October 1976 and ending in October 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'. All return estimates are annualized.

	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	2.8	11.71	10.91	8.11	2.24	4.19	14.67	15.56	11.37	3.57
M	8.23	7.8	8.55	0.32	0.10	4.27	11.34	12.91	8.63	4.19
H	0.19	6.63	7.74	7.54	2.17	-2.61	7.69	8.57	11.18	5.12
H-L	-2.6	-5.08	-3.17			-6.8	-6.98	-6.99		
[t]	-0.77	-2.6	-1.35			-2.61	-4.08	-3.99		
Panel B: Capital age and size sorted portfolios										
L	-2.78	10.01	14.32	17.1	5.42	8.31	18.17	20.63	12.33	4.21
M	0.44	9.88	11.33	10.89	4.79	-2.29	9.74	11.52	13.81	3.41
H	5.52	7.63	8.52	3.01	1.2	4.72	8.77	9.53	4.81	3.6
H-L	8.3	-2.37	-5.8			-3.59	-9.41	-11.11		
[t]	2.09	-0.67	-1.49			-0.87	-2.93	-2.98		
Panel C: Capital age and book-to-market sorted portfolios										
L	1.99	5.27	7.58	5.6	1.19	-7.82	3.34	6.91	14.73	4.57
M	3.5	8.18	9.95	6.46	2.56	3.56	10.99	12.14	8.58	4.56
H	8.84	12.29	13.75	4.92	1.50	12.85	17.73	17.68	4.84	1.70
H-L	6.85	7.01	6.17			20.66	14.4	10.77		
[t]	1.27	2.5	1.92			5.45	5.82	3.85		

Table 8: Asset Pricing Tests with Double Sorted Portfolios

This table reports annualized alphas of standard asset pricing factor models (CAPM and Fama-French 5 factors) across 3×3 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. Portfolios are rebalanced at a quarterly frequency starting in October 1976 and ending in October 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	-6.89	4.19	4.13	11.02	3.35	-4.68	6.76	8.22	12.9	4.11
M	-1.28	1.06	3.18	4.46	1.63	-4.55	3.88	5.91	10.46	5.52
H	-10.05	-1.18	0.15	10.2	3.21	-12.44	-0.5	0.89	13.33	6.53
H-L	-3.16	-5.37	-3.98			-7.75	-7.27	-7.33		
[t]	-0.93	-2.73	-1.69			-2.97	-4.19	-4.15		
Capital age and size sorted portfolios										
L	-11.05	3.08	7.92	18.97	6.01	0.2	11.25	14.24	14.04	4.11
M	-9.57	1.78	3.86	13.44	6.6	-12.06	1.74	4.1	16.16	8.32
H	-3.31	1.05	3.25	6.56	3.17	-4.65	1.45	2.6	7.25	3.76
H-L	7.74	-2.03	-4.68			-4.86	-9.8	-11.64		
[t]	1.94	-0.58	-1.24			-1.16	-3.01	-3.08		
Capital age and book-to-market sorted portfolios										
L	-9.66	-2.28	1.79	11.46	2.96	-18.12	-5.36	-0.27	17.84	6.17
M	-5.2	1.36	4.28	9.48	4.27	-5.29	3.46	4.96	10.25	5.96
H	-0.61	4.82	5.75	6.36	1.98	4.44	10.5	10.76	6.32	2.21
H-L	9.05	7.1	3.95			22.55	15.86	11.03		
[t]	1.71	2.53	1.28			6.08	6.27	3.91		
Panel B: FF5 5-factor model										
	Fama-French 5 Alphas					Fama-French 5 Alphas				
Capital age and investment rate sorted portfolios										
L	-7.01	1.5	-1.81	5.19	1.73	-1.93	4.01	3.61	5.54	2.01
M	1.54	-2.08	-0.57	-2.11	-0.86	-5.14	-0.2	0.84	5.98	3.46
H	-5.28	-3.09	-3.34	1.94	0.78	-9.81	-2.61	-1.91	7.9	4.56
H-L	1.73	-4.59	-1.52			-7.88	-6.62	-5.52		
[t]	0.57	-2.41	-0.63			-3.23	-4.56	-3.27		
Capital age and size sorted portfolios										
L	-8.56	1.52	5.57	14.13	4.53	3.94	10.5	12.49	8.55	2.46
M	-8.45	-2.66	-2.02	6.44	4.7	-10.99	-2.66	-1.35	9.64	6.77
H	0.29	-2.08	-0.34	-0.62	-0.38	-3.3	-2.36	-2.19	1.12	0.78
H-L	8.85	-3.59	-5.9			-7.24	-12.85	-14.68		
[t]	2.92	-1.51	-2.05			-1.93	-5.08	-4.58		
Capital age and book-to-market sorted portfolios										
L	-2.17	-3.6	-2.91	-0.74	-0.25	-13.56	-5.89	-3.91	9.65	4.55
M	-5.15	-1.91	0.19	5.34	2.89	-5.14	-0.51	-0.19	4.95	3.36
H	-1.7	-0.39	-0.25	1.45	0.47	4.07	6.25	5.69	1.62	0.56
H-L	0.47	3.21	2.66			17.64	12.13	9.6		
[t]	0.11	1.68	1.16			6.07	6.25	4.32		

Table 9: Cross-Sectional Regressions

This table reports the results of Fama-MacBeth regressions of individual stock excess returns on their lagged value and firms' characteristics. 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. All the control variables are divided by their unconditional standard deviation. The sample period is from October 1976 to December 2016.

	[1]	[2]	[3]	[4]	[5]	[6]
Lagged return	-0.77	-0.78	-0.81	-0.78	-0.81	-0.84
[t]	-10.16	-10.89	-10.75	-10.18	-10.77	-11.83
Capital age (log)	0.40	0.42	0.31	0.34	0.37	0.26
[t]	6.76	7.52	5.22	5.44	6.85	5.18
Size (log)		-0.27				-0.25
[t]		-3.10				-3.08
BM (log)			0.41			0.27
[t]			7.47			5.57
IK				-0.20		-0.18
[t]				-6.18		-6.57
ROE					0.24	0.33
[t]					3.93	6.91
Observations	483	483	483	483	483	483
R^2	0.014	0.024	0.020	0.015	0.023	0.033

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. For both set of test assets, we report the rank restriction test W (allowing for conditional heteroskedasticity) and its asymptotic p-value (p-val) of the null that $E[x_t(1, f_{it})]$ has a column rank of one, where x_t is the matrix of test assets and f_{it} is a risk factor. In Panel A we report the pricing error (α_i) and the covariance (Cov_i) of each portfolio with the different macroeconomic shocks implied by a two-factor model with MKT and one macroeconomic shock. In Panel B and Panel C we report the first-stage results of a GMM estimation of a one-factor model using MKT, a two-factor using MKT and the technology frontier shock proxy, and a three factor model using MKT, the technology frontier shock proxy and one additional macroeconomic shock, respectively. For each 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 from the third quarter in 1976 to the fourth quarter in 2014. The macroeconomic shocks include the proxy for the aggregate frontier shock measured as the growth rate of the number of new technology standards (Frontier), the log change in real GDP (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 (Liquidity), the log change in the BAA-AAA spread, the change in macroecomonic uncertainty (Jurado, Ludvigson, and Ng (2013)), and a proxy for investment-specific technology shocks based on the relative price of capital goods (IST, Papanikolaou (2011)).

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

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

Portfolio		Frontier	GDP	TFP	cay	Liquidity	Credit	Uncertainty	IST
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	α_i	-2.02	-6.96	-8.30	-4.80	-10.15	-10.51	-10.52	-10.05
	$[t]$	-1.14	-1.51	-2.38	-1.61	-4.51	-4.54	-4.29	-4.70
	Cov_i	-1.43	-0.19	-0.02	-0.07	0.08	-0.15	-0.07	-0.01
	$[t]$	-2.02	-2.99	-1.00	-2.55	0.32	-0.28	-0.85	-0.30
3	α_i	0.73	4.42	1.11	3.27	-1.53	-0.14	-0.56	0.82
	$[t]$	0.22	1.44	0.36	1.19	-1.00	-0.13	-0.32	0.75
	Cov_i	0.16	-0.06	0.00	-0.04	0.04	-0.47	-0.17	-0.01
	$[t]$	0.41	-1.17	-0.27	-1.69	0.30	-1.59	-1.97	-0.82
5	α_i	-3.11	-3.30	-1.01	-2.53	-0.15	-0.36	0.53	-0.01
	$[t]$	-1.79	-1.42	-0.52	-1.55	-0.17	-0.36	0.45	-0.01
	Cov_i	0.45	0.00	-0.03	0.00	0.17	-0.07	-0.08	0.00
	$[t]$	1.56	-0.09	-0.37	-0.20	1.22	-0.53	-1.66	0.38
7	α_i	1.18	0.14	-1.24	1.12	3.99	3.89	2.92	3.61
	$[t]$	0.68	0.07	-0.78	0.58	3.38	2.97	2.41	2.60
	Cov_i	0.21	0.03	0.00	0.02	-0.01	0.39	0.03	0.02
	$[t]$	0.64	0.90	0.19	1.71	-0.09	2.51	0.61	1.12
10	α_i	0.35	2.05	3.63	4.31	5.22	5.78	5.19	4.28
	$[t]$	0.16	0.83	1.40	1.39	3.55	3.33	3.11	3.06
	Cov_i	0.78	0.05	0.01	0.00	0.15	-0.52	-0.03	0.02
	$[t]$	1.80	1.33	0.62	-0.08	1.18	-1.59	-0.76	0.73
OMY	α_i	2.37	9.01	11.94	9.11	15.37	16.29	15.71	14.33
	$[t]$	1.03	1.57	2.37	1.84	4.53	4.36	4.28	4.71
	Cov_i	2.22	0.21	0.03	0.07	0.06	-0.28	0.05	0.01
	$[t]$	2.32	2.98	1.19	2.09	0.21	-0.48	0.46	0.46

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

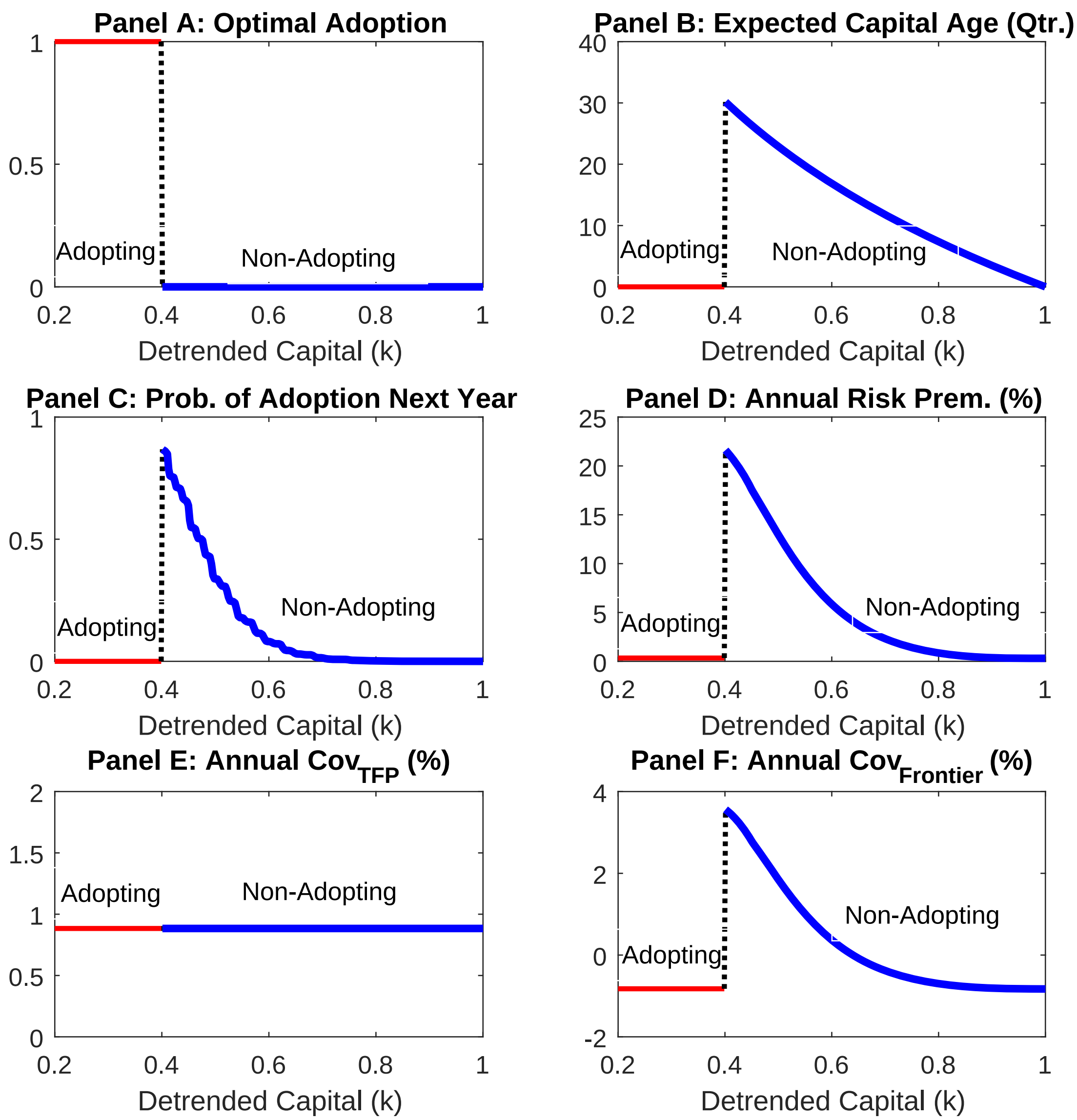
Panel B: GMM estimation with capital age sorted portfolios

	MKT	Frontier	GDP	TFP	cay	Liquidity	Credit	Uncertainty	IST
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
b_M	0.18	0.20	0.18	0.18	0.35	0.20	0.25	0.31	-0.01
$[t]$	2.16	1.22	1.08	1.13	2.05	0.52	1.33	1.66	-0.03
b_F		1.87	1.52	1.63	1.25	1.87	1.85	1.81	1.75
$[t]$		2.79	1.84	2.63	2.15	2.79	2.81	2.88	2.76
b_{MACRO}			0.73	-0.74	1.12	0.01	0.18	0.41	0.80
$[t]$			0.66	-1.07	1.79	0.01	0.37	0.83	1.41
MAE	3.44	1.80	1.72	1.72	1.44	1.8	1.84	1.68	1.75
Rank test for individual factors									
W	94.64	17.18	3.82	8.63	19.93	33.23	38.10	31.22	16.00
p-val	0.00	0.05	0.92	0.47	0.02	0.00	0.00	0.00	0.07

Panel C: GMM estimation with a broader set of test assets

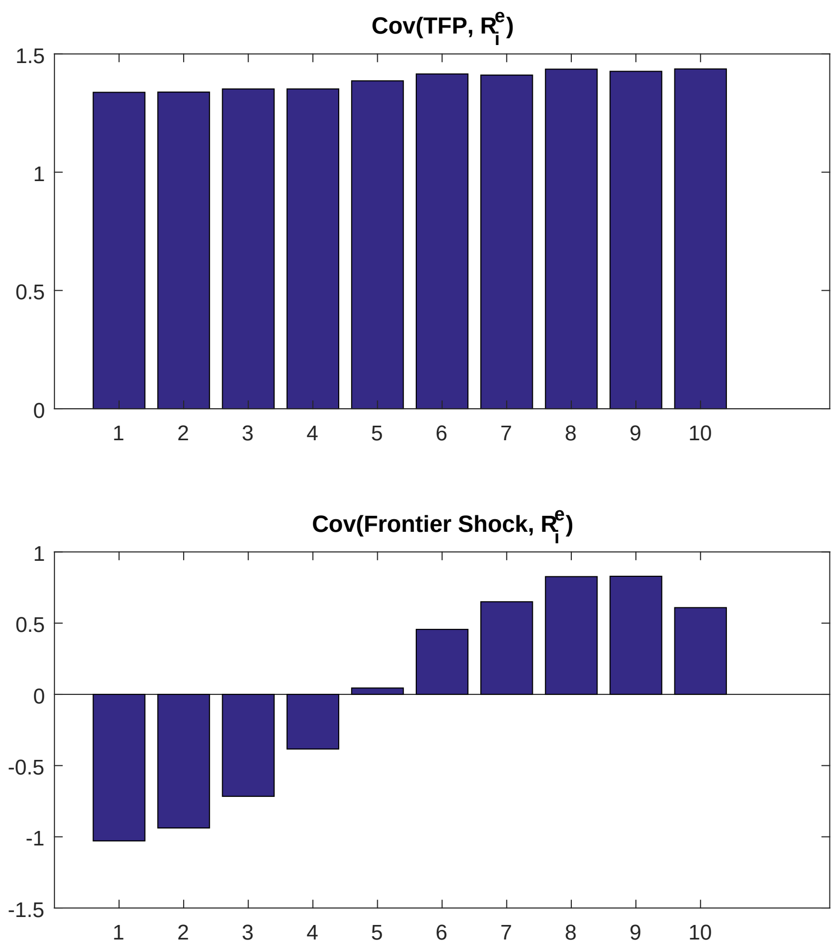
	MKT	Frontier	GDP	TFP	cay	Liquidity	Credit	Uncertainty	IST
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
b_M	0.23	0.22	0.21	0.21	0.32	0.44	0.36	0.38	0.17
$[t]$	2.72	2.08	1.98	1.71	2.36	1.64	2.80	2.96	1.45
b_F		0.91	0.88	0.75	0.96	0.99	0.96	0.86	1.02
$[t]$		2.68	2.46	1.70	2.51	3.01	2.32	2.11	2.78
b_{MACRO}			0.20	-0.85	0.87	-0.43	0.51	0.58	-0.02
$[t]$			0.55	-1.80	1.47	-0.81	1.52	1.39	-0.05
MAE	2.44	2.16	2.16	1.6	1.8	1.96	1.76	1.84	2.06
Rank test for individual factors									
W	436.87	69.83	103.97	44.36	64.06	137.24	133.97	154.91	79.89
p-val	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00

Figure 1: Policy functions



This figure reports the optimal adoption policy, the expected capital age in quarters, the probability of adoption next year, the annual stock risk premium of a firm, the annualized covariance between stock returns and aggregate productivity shocks (in percentages), and the annualized covariance between stock returns and the technology frontier shocks (in percentages) as functions of the detrended capital (k). We set all shocks at their long run means.

Figure 2: Aggregate productivity shock and aggregate technology frontier shock covariances



This figure reports the risk exposures (covariances) of the excess returns of the 10 capital age portfolios, with respect to the aggregate productivity shock (TFP), and the aggregate technology frontier shock, using data simulated from the model. The reported statistics for the model are obtained as averages from 100 samples of simulated data, each with 5,000 firms and 120 quarterly observations.

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 October 1976 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. Columm O-Y reports the difference between the top 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	3	5	7	Old	O-Y
Panel A: Portfolio returns and Sharpe ratios						
E[R^e]	1.60	5.53	7.02	9.13	10.08	8.47
t-stat	0.36	1.84	2.41	4.03	4.94	2.41
SR	0.06	0.26	0.39	0.49	0.74	0.43
Panel B: CAPM alphas						
mae = 3.71						
α	-8.56	-2.49	-0.67	2.67	4.84	13.40
t-stat	-3.65	-1.61	-0.55	2.29	3.89	4.50
MKT	1.40	1.11	1.06	0.89	0.72	-0.68
t-stat	24.79	36.57	35.09	25.16	17.96	-7.95
R^2	0.71	0.78	0.84	0.79	0.67	0.28

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 October 1976 and ending in October 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	9.99	11.48	10.82	0.83	0.28	1.40	3.96	4.19	2.79	1.01
3	5.39	7.56	8.86	3.47	1.06	-4.10	0.79	3.45	7.55	2.71
High IK	1.40	6.21	8.58	7.18	2.15	-8.59	-1.80	1.19	9.78	3.14
H-L	-8.59	-5.27	-2.24			-9.99	-5.75	-3.00		
	-2.75	-2.62	-0.83			-3.21	-2.84	-1.12		
	FF5 α					HXZ α				
Low IK	-1.16	0.26	-0.82	0.34	0.13	1.54	0.73	-0.74	-2.29	-0.86
3	-0.70	-2.22	-0.59	0.10	0.05	0.09	-1.76	-0.43	-0.52	-0.21
High IK	-3.69	-3.30	-1.19	2.49	0.93	-2.29	-2.20	-0.55	1.74	0.60
H-L	-2.53	-3.56	-0.37			-3.83	-2.93	0.19		
	-0.99	-1.78	-0.14			-1.41	-1.46	0.07		

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	-0.51	9.52	13.26	13.77	4.56	-8.85	2.64	6.72	15.57	5.12
3	0.57	9.52	11.94	11.38	5.00	-9.42	1.31	4.69	14.11	7.11
Big	5.86	7.48	8.77	2.91	1.24	-2.66	0.84	3.52	6.18	3.17
BMS	6.37	-2.04	-4.49			6.19	-1.79	-3.20		
	1.56	-0.59	-1.14			1.52	-0.52	-0.84		
	FF5 α					HXZ α				
Small	-6.66	1.10	4.62	11.28	3.72	-2.15	4.37	8.46	10.61	3.39
3	-8.42	-3.03	-1.08	7.34	5.55	-5.77	-1.31	0.00	5.77	3.59
Big	0.26	-2.09	-0.38	-0.64	-0.42	1.55	-1.84	-0.23	-1.78	-1.10
BMS	6.92	-3.18	-5.00			3.70	-6.20	-8.69		
	2.25	-1.34	-1.76			1.17	-2.76	-3.21		

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	2.77	4.58	8.16	5.39	1.23	-7.98	-2.97	2.31	10.29	2.71
	4.16	8.26	9.78	5.63	2.32	-4.29	1.37	4.17	8.45	3.96
Value	9.24	13.28	14.69	5.45	1.54	-0.09	5.75	6.82	6.91	1.98
VMG	6.47	8.70	6.53			7.88	8.71	4.50		
	1.17	2.97	2.22			1.44	2.98	1.58		
	FF5 α					HXZ α				
Growth	-0.37	-4.62	-2.27	-0.64	-1.95	2.63	-0.35	3.38	0.75	0.21
	-5.09	-1.79	0.17	5.25	2.82	-5.79	0.23	4.74	10.54	5.67
Value	-2.58	0.17	1.63	4.21	1.27	-8.24	7.19	6.20	14.44	4.33
VMG	-2.21	4.79	3.90			-10.87	7.54	2.83		
	-0.51	2.44	1.80			-2.30	3.14	1.12		

Table A3: Capital Age Sorted Portfolios and Tests of the Hou-Xue-Zhang factor model

This table reports average annualized excess return and test results using the Hou-Xue-Zhang factor model across ten value and equal weighted age-sorted portfolios in the data. Portfolios are rebalanced at a quarterly frequency starting in October 1976 and ending in October 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'.

	Value weighted						Equal weighted					
	Y	3	5	7	O	OMY	Y	3	5	7	O	OMY
	HXZ test: MAE=1.61						HXZ test: MAE=2.57					
Alpha	-4.68	-1.20	-3.61	-0.92	0.73	5.41	-4.60	1.45	1.97	2.20	2.71	7.31
[t]	-1.80	-0.76	-3.02	-0.67	0.68	2.11	-1.22	0.68	1.12	1.36	1.46	2.61
MKT	1.31	1.02	1.03	0.96	0.86	-0.45	1.09	1.01	0.98	0.98	0.95	-0.14
[t]	23.54	30.76	34.20	36.14	35.97	-7.64	17.37	22.10	24.27	25.52	19.26	-2.58
ME	0.35	0.24	0.03	-0.05	-0.08	-0.42	0.72	0.76	0.71	0.62	0.64	-0.08
[t]	3.01	3.42	0.57	-0.85	-1.20	-4.03	4.71	6.49	6.38	5.62	5.45	-1.13
IA	-0.91	-0.26	0.11	0.24	0.63	1.54	-0.50	0.13	0.29	0.47	0.55	1.05
[t]	-6.32	-2.99	1.67	3.40	8.08	9.43	-1.82	1.01	2.37	4.02	4.30	4.80
ROE	-0.26	0.06	0.20	0.31	0.02	0.29	-0.82	-035	-0.21	-0.17	-0.20	0.62
[t]	-2.59	0.98	3.65	6.10	0.40	2.35	-4.07	-3.60	-2.38	-1.87	-1.89	3.56
R^2	0.81	0.81	0.82	0.82	0.75	0.58	0.77	0.85	0.87	0.87	0.84	0.42

Table A4: Asset Pricing Tests with Double Sort Portfolios

This table reports annualized alphas produced using the Hou-Xue-Zhang factor model across 3×3 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. Portfolios are rebalanced at a quarterly frequency starting in October 1976 and ending in October 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]
Capital age and investment rate sorted portfolios										
L	-3.61	1.75	-1.4	2.21	0.73	3.67	7.3	5.74	2.07	0.72
M	2.34	-1.64	-0.4	-2.74	-1.1	-1.67	1.65	2.36	4.03	2.22
H	-3.71	-2.11	-2.09	1.62	0.58	-6.25	-0.72	-0.07	6.18	3.25
H-L	-0.1	-3.86	-0.69			-9.92	-8.02	-5.81		
[t]	-0.03	-1.98	-0.29			-4.03	-5.71	-3.49		
Capital age and size sorted portfolios										
L	-4.19	4.99	8.93	13.12	4.04	9.34	14.39	15.65	6.31	1.77
M	-5.89	-0.95	-0.9	4.98	3.04	-7.44	-0.52	0.21	7.65	4.74
H	1.42	-1.74	-0.26	-1.68	-0.96	-2.38	-1.49	-1.57	0.8	0.5
H-L	5.61	-6.72	-9.18			-11.72	-15.88	-17.22		
[t]	1.8	-3	-3.34			-3.1	-6.36	-5.52		
Capital age and book-to-market sorted portfolios										
L	0.61	0.56	1.97	1.36	0.37	-15.83	-1.88	1.28	17.11	6.37
M	-6.81	0.36	4.82	11.63	6.22	-5.28	1.98	4.36	9.64	6.27
H	-6.36	5.26	4.1	10.47	3.38	1.51	11.06	11.28	9.77	3.41
H-L	-6.97	4.7	2.13			17.34	12.94	10.00		
[t]	-1.47	1.97	0.81			5.34	5.97	4.00		

Table A5: Pooled Cross-Sectional Regressions

This table reports the results of cross sectional regressions of individual stock excess returns on their lagged value and firms' characteristics using 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 October 1976 to December 2016.

	[1]	[2]	[3]	[4]	[5]	[6]
Lagged return	-0.90	-0.78	-0.93	-0.90	-0.90	-0.79
[t]	-12.20	-10.94	-12.59	-12.22	-12.20	-11.21
Capital age (log)	0.64	0.21	0.48	0.57	0.64	0.17
[t]	12.06	3.70	9.23	10.72	12.29	3.05
Size (log)		-3.50				-3.45
[t]		-19.25				-18.37
BM (log)			0.99			0.21
[t]			15.48			3.49
IK				-0.13		-0.04
[t]				-5.43		-2.00
ROE					0.02	0.28
[t]					0.44	8.94
Observations	941,150	941,150	941,150	941,150	941,150	941,150
R^2	0.146	0.151	0.148	0.146	0.146	0.152
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes