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Beta and firm age[☆]

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ABSTRACT

We document a robust pattern of beta declining over the age of a firm. We find that changes in systematic risk via firm characteristics and life-cycle stages are insufficient to explain this pattern. Moreover, standard proxies for the quantity and quality of information also explain this pattern only partially. To fully explain this pattern we rely on the increasingly important role of familiarity in financial decision making: familiarity is a determinant of beta and firm age is a proxy for the degree of familiarity that investors feel toward individual stocks. To illustrate the implication of our findings, we document that when we control for firm age there is support for the CAPM and its use as an input for the cost of equity capital calculation.

1. Introduction

Despite criticism, the Capital Asset Pricing Model (CAPM) is used extensively in finance. For example, Graham and Harvey (2001) report that 73% of firms use the CAPM to estimate the cost of equity capital. The only firm-specific input of the CAPM is beta. Understanding the beta of a company is important for a vast amount of business applications, including measuring the cost of equity capital for valuing corporate projects, measuring risk-adjusted returns, measuring portfolio risk, and even in litigation associated with public securities where an estimate of market efficiency or loss damages must be produced.

There is a vast literature on the empirical failure of beta to capture the behavior of stock returns. Some of the stylized facts about empirical beta are that (1) measured betas tend to regress toward one (Blume, 1975); (2) larger portfolios have more stable betas than small portfolios and estimates of beta are more precise for portfolios than for single stocks (Blume, 1970); (3) betas estimated as a function of fundamental firm data might be better at predicting future beta than simple historical regressions of company returns on market returns (Beaver et al., 1970); (4) beta is time-varying and historically measured beta tends to be a bad predictor of future beta (Blume, 1975; Ferson and Harvey, 1991; Jagannathan and Wang, 1996); and (5) beta cannot explain the excess returns of small-cap stocks and value stocks (Fama and French, 1992). High frequency data could be used to resolve some of the above issues, but non-synchronous trading adds another layer of complications (Bollerslev and Zhang, 2003).

In this paper, we focus on an additional pattern that may appear intuitive and familiar to some researchers and practitioners but remains untested and undocumented in the academic literature; the measured beta declines over the age of a firm. There are many reasons why beta could be time-varying and in particular could be higher for younger firms. We consider four possible explanations for this pattern.

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The first, most straightforward explanation is that important determinants of beta related to firm characteristics change over age and consequently lower the systematic risk. Beaver et al. (1970) show that variables such as earnings variability and leverage are important determinants of beta and systematic risk. Another often mentioned determinant of beta is liquidity costs (e.g., Amihud and Mendelson (2000) and Jacoby et al. (2000)). If liquidity improves as a firm matures, then this could explain the decay of beta over age. We find, however, that these variables are not adequate to explain the pattern of this decline. The decline in beta over firm age remains even after we control for variables known to be associated with systematic risk such as size, book-to-market, and other firm characteristics. In particular, we find that indicators of leverage and the liquidity measures do not explain the decline in beta. Considering this result, together with the fact that measured beta is a poor predictor of future stock returns,[1] it is clear that a characteristics-based explanation does not account for our pattern.

The second explanation is based on the firm life-cycle model popularized by the financial accounting research such as DeAngelo et al. (2006), Dickinson (2011), and Faff et al. (2016). In the firm life-cycle model, firms go through several stages of development, each stage with a distinct risk and return profile. While age is not a perfect proxy of life-cycle stages, one still obtains a significant correlation between beta and age under the life-cycle model. We find, however, that this explanation is insufficient. Beta exhibits a U-shaped pattern over firm life cycle, which is distinct from the pattern over firm age. Moreover, we find that age remains significant when we include both age and life-cycle proxies in the regressions.

The third explanation is that changes in the amount and quality of information over firm age generate declining beta over time. Ball and Kothari (1991) and Patton and Verardo (2012) show that beta changes as investors update their assessments of systematic risk when new information is released around earnings announcement days. Lambert et al. (2007) show that improvements in information quality by firms affect the beta and the cost of capital. A related idea focuses on information asymmetry rather than the amount and quality of information. Williams (1977) was the first to analyze the effect of heterogeneous beliefs on the CAPM.[2] Easley and O'Hara (2004) and Botosan et al. (2004) show that differences in the composition of information between public and private information affects the cost of capital, with investors demanding a higher return to hold stocks with greater private (and correspondingly less public) information.[3] Doukas et al. (2006) clarify the empirical link between divergence of opinion and future stock returns and find that a positive abnormal return exists for stocks with high analyst difference of opinion.

This line of research suggests that as firms get older, the amount and quality of information improves, and systematic risk decreases. The reason is that the accumulation of information affects investors' assessment of the underlying distribution or data generating process (DGP), rather than affecting the DGP itself. Thus, the explanation is that the systematic risk of high-information stocks is lower, not because their cashflow is less correlated with the market cashflow, but because investors know more about the correlation of these stocks. Therefore, the theory of information is related to the theory of estimation risk, where the central role is what investors know about the DGP not what the DGP actually is. Barry and Brown (1985) and Clarkson and Thompson (1990) emphasize the effect of estimation risk on systematic risk.[4] We find that these information-based explanations are relevant, but insufficient. When we include the information proxies suggested by these prior studies in our analysis, these variables only partially explain the decline of beta over firm age.

In order to entirely explain the declining beta over age, we turn to the growing literature on the role of familiarity on asset prices. Huberman (2001), Grinblatt and Keloharju (2001), Massa and Simonov (2006), Cao et al. (2011), and Boyle et al. (2012) emphasize the role of familiarity in financial decision making. Familiarity is distinct from estimation risk; the latter is acquired through accumulating more information whereas the former is acquired through holding information for a longer time. Thus, age is likely to be a significant indicator of the degree of familiarity that aggregate investors feel toward individual stocks. Our empirical analysis is consistent with this last explanation for the decline in beta. Age, a proxy for familiarity, remains an important determinant of beta after controlling for the previous explanations using firm characteristics, life-cycle stages, and information variables.

In order to formalize our intuition regarding familiarity and beta, we propose a simple equilibrium model of asset prices, incorporating key elements from the models of Clarkson and Thompson (1990) and Boyle et al. (2012). In our model, as in the model of Clarkson and Thompson (1990), estimation risk is determined by the amount of information, which in our model is a function of the number of analysts following each stock. A decline in estimation risk is associated with higher equilibrium prices, lower expected returns, and lower beta. As in Boyle et al. (2012), the "unfamiliarity premium" is reflected by an investor's decision with attention to the worst possible scenario. One can think of this as a downside loss criterion. As firms get older, the worst case scenario becomes less severe. Thus, older firms have a smaller unfamiliarity premium, higher prices, lower expected returns, and lower beta.

The empirical analysis of this paper can be summarized as follows. We run regressions of betas on age at the stock level and portfolio level, where we sort stocks into different age groups. We find a significant and negative relation between age and beta. This decline in beta persists for almost 100 years (along the age dimension). After documenting this pattern, we investigate whether we can explain it using different proxies for systematic risk including firm characteristics, life-cycle stages, and various measures

[1] See, for example, Fama and French (1992). We confirm this fact in Section 5 in the context of long-term returns.

[2] More recently, Lambert and Verrecchia (2015) demonstrate in a CAPM framework that information asymmetry can have an impact on cost of capital through its association with market illiquidity.

[3] The risk is systematic risk because uninformed traders always hold too many stocks with bad news, and too few stocks with good news. Adding more stocks to the portfolio cannot remove this risk because the uninformed are always holding the wrong stocks.

[4] There is a debate on whether estimation risk is diversifiable. As emphasized by Clarkson et al. (1996), estimation risk is not entirely diversifiable if the market return is correlated with estimation risk. In other words, if high estimation-risk securities constitute a significant fraction of the market portfolio, estimation risk remains non-diversifiable. Whether this is the case is a question to be settled via empirical studies. Given the presence of a large number of young firms in any given time, estimation risk is likely to remain non-diversifiable. Our empirical results support this prediction.

of information. We find that age remains significant after including many different explanatory variables. When we use, as a proxy for familiarity, an information variable that accumulates past information, we find that it subsumes the explanatory power of age. We interpret these results as showing that age is a proxy of familiarity and an important driver of the decline in beta.

We conduct several robustness checks. First, we find similar results when we include additional determinants of beta, such as operating leverage and momentum (Cosemans et al., 2016), and when we control for industries. Second, we confirm that the pattern related to age is also present when we use the unlevered beta of firms. Third, we use equally-weighted beta portfolios rather than value-weighted beta portfolios and find comparable results. Fourth, we include a squared age term to capture a possible non-linear relationship between beta and age. The squared term coefficient is statistically significant, but very small and not economically significant. Fifth, we conduct the analysis on a subsample of data and show that the effect of age on beta is stronger for younger firms. Lastly, to address concerns about the impact of firms leaving the sample, we exclude non-surviving firms and find that the age–beta relationship remains intact.

The final part of our empirical analysis concerns the implication of our findings for the cost of equity capital calculation. Indeed, one direct implication is that, using the CAPM, the decline in beta with age leads to a decline in the cost of equity capital. The main issue is that, although the CAPM is used extensively in practice to estimate the cost of equity capital, it has been generally rejected in empirical academic studies. To address this issue, we compare the ability of the CAPM to explain the cross-section of holding-period expected returns à la Cohen et al. (2009), when controlling for the age of the firm. We document that while there is an insignificant relationship between expected return and beta when age is ignored, this relationship becomes positive and significant when we control for age. We also advocate for the use of betas computed from a portfolio of stocks with similar age for the cost of equity capital calculation.

In many ways, this paper is similar in spirit to Clarkson and Thompson (1990). They report that stock market beta declines with the age of the firm during the first year that a company is listed on a stock exchange. Our paper shows that the decline in beta is not limited to the first year after an IPO. In fact, we show that the decline in beta continues for 100 years. Compared to Clarkson and Thompson, we consider a more comprehensive set of alternative explanations for the decline in beta. In particular, we consider firm characteristics, life-cycle stages, information variables, and familiarity as possible drivers of this pattern. Finally, we explore the implications of our findings on tests for the CAPM when considering a long-horizon perspective.

This paper is also related to the literature that documents that information and uncertainty effects have an impact on beta and the cost of capital. A large finance and accounting literature (e.g., Botosan et al. (2004), Easley and O'Hara (2004), Hughes et al. (2007), and Lambert et al. (2007, 2011)) examines the relationship between various information attributes (e.g., information asymmetry and quality) and the cost of capital. Our work is connected to this information literature in that we show that the decline in beta over age is not explained by established information measures. We also show, theoretically and empirically, that age, serving as a proxy for familiarity, is a determinant of beta.

There are relevant implications of our findings. First, practitioners that use beta as a measurement for the cost of capital or as a risk management tool should pay attention to age, as it can improve the beta estimate. Second, the finding that controlling for age is important for explaining the cross-section of holding-period expected returns provides a justification for the continued use of the CAPM in capital budgeting and implies that the decline of beta over age has an impact on the cost of equity capital as measured by the CAPM. Capital budgeting ultimately involves measuring long-term risk correctly. Changing betas over long horizons are pivotal to this process. Last, the findings of this paper have important implications for the finance and accounting literature that investigates the cost of capital and various information attributes affecting the cost of capital. Several papers (e.g., Gebhardt et al., 2001; Claus and Thomas, 2001; Gode and Mohanram, 2003; Hou et al., 2012) have recommended an implied-cost-of-capital approach to measure the cost of capital instead of using CAPM. We suggest that the use of CAPM to measure the cost of capital is appropriate if we adjust for the age effect by using betas computed from a portfolio of firms with similar age.

The rest of the paper is organized as follows. Section 2 presents a simple model that illustrates how information and age affects beta via estimation risk and the familiarity effects; Section 3 discusses the data and construction of key variables to be used in the empirical analysis; Section 4 discusses the empirical findings of age and beta; Section 5 discusses the asset pricing implications of age and capital budgeting practical implications; and Section 6 concludes.

2. Familiarity, estimation risk, and beta

As explained in the introduction, there are several explanations for the decrease in beta over time. First, the decline of beta may be related to fundamentals of a firm that change over time. Second, firm age is a proxy for life-cycle stages. Third, the type of information changes over time and/or the disagreement decreases as investors learn more about a company's systematic risk. Lastly, estimation risk and investor familiarity may affect beta. In this section we want to further discuss this last explanation and provide a simple model to support it. Although we cannot rule out that age reflects an estimation risk component not captured by other information variables used in this study, we posit that age is a measure of investor familiarity with a given stock and one of the determinants of the time variation of beta.

There is a large literature on estimation risk (also called parameter uncertainty) in the context of the CAPM beta. Barry (1978), Barry and Brown (1985), Coles and Loewenstein (1988), Clarkson (1986), and Clarkson and Thompson (1990) have considered beta estimation by investors who face uncertainty over the exact parameters of the joint return distribution. Handa and Linn (1993) consider the same issue within the framework of the arbitrage pricing theory. Kumar et al. (2008) construct a model where investors are uncertain about the parameters of the return distribution and also about the precision or quality of firm-specific information. Armstrong et al. (2013) present an alternative model focusing on the dividend process. These models suggest that estimation risk affects the equilibrium expected returns as investors construct portfolios considering estimation risk. According to this perspective, the cost of equity capital calculation may improve if an additional factor representing estimation risk is included.[5]

There is also a growing literature examining the consequence of familiarity on investment decisions and equilibrium asset prices. Huberman (2001) observed that geographical proximity influences individuals' portfolio choices; Grinblatt and Keloharju (2001) found that cultural proximity influences portfolios; Massa and Simonov (2006) found that individuals' portfolios also tilted toward stocks closely related to their non-financial income. These observations are examples of general tendency to tilt portfolios toward familiar assets. Consistent with this interpretation, Cao et al. (2011) and Boyle et al. (2012) present theories of unfamiliarity premium building on the larger literature on ambiguity aversion.

Below, we study a simple equilibrium model that highlights the consequence of estimation risk and familiarity on asset prices. We borrow the key elements of estimation risk from Clarkson and Thompson (1990) and of familiarity from Boyle et al. (2012). In this model, estimation risk is determined by the amount of information available for each stock, which in turn is determined by the number of analysts. That is, when a large number of analysts follow a stock, investors have more information, which reduces estimation risk. This will increase the equilibrium price, makes expected returns of this stock lower, and as a consequence CAPM beta becomes smaller. Familiarity is distinct from estimation risk. Familiarity is obtained not by accumulating more information but by holding the information longer. The age of a firm is good proxy for familiarity when we abstract from differences across individual investors. When a firm is around longer, it is more likely that investors feel more familiar toward the firm. Thus, when a firm is older, investors feel more familiar with the firm, which reduces the unfamiliarity premium, makes expected returns lower, and as a consequence CAPM beta becomes smaller.

2.1. Setup

There are two firms denoted by i and j. At the end of the current period, the two firms pay liquidating dividends. We denote the dividend amounts by D_i and D_j. The number of shares outstanding for each firm is one. So the dividends per share equal D_i and D_j. We assume that the true distribution, i.e., the data generating process (DGP), of the dividend amounts is normal:

$$D \sim N(\nu, \Omega) \tag{1}$$

where D is a vector made of D_i and D_j. To focus on the effect of estimation risk and familiarity, we assume that the covariance is zero and the variances of two dividends are identical. That is,

$$\Omega = \begin{pmatrix} \omega^2 & 0 \\ 0 & \omega^2 \end{pmatrix} \tag{2}$$

Risk-free bonds are available. One share of the bond pays \$1 at the end of the current period. We assume that the net number of bond shares outstanding is zero.

The current share prices of the two stocks and the risk-free bond are denoted by P_i, P_j, and P_f. At the end of the period, excess returns for the two stocks are calculated as $R_i = D_i/P_i - 1/P_f$ and $R_j = D_j/P_j - 1/P_f$. Since D_i and D_j are jointly normal, the true distribution of excess returns is also normal. So we may write:

$$R \sim N(\mu, \Sigma) \tag{3}$$

where R is a vector made of R_i and R_j. Note that

$$\mu = \begin{pmatrix} \frac{\nu_i}{P_i} - \frac{1}{P_f} \\ \frac{\nu_j}{P_j} - \frac{1}{P_f} \end{pmatrix} \tag{4}$$

and

$$\Sigma = \begin{pmatrix} \frac{1}{P_i^2}\omega^2 & 0 \\ 0 & \frac{1}{P_j^2}\omega^2 \end{pmatrix} \tag{5}$$

An interesting feature of this type of model is that the true data generating process $N(\mu, \Sigma)$ does not determine equilibrium prices. Equilibrium prices are determined from the predictive distribution, which in general is different from the true distribution.[6] As investors consider estimation risk and familiarity in their decision making process, they require extra compensation for holding securities with high estimation risk or a low degree of familiarity. We assume the existence of a representative agent. The representative agent forms the predictive distribution of excess returns, based on which the agent creates an optimal portfolio. From the agent's optimal portfolio, we can determine the demand for each asset. By comparing the demand to the supply, we can determine the equilibrium prices. Once equilibrium prices are determined, the return distribution can be determined, from which CAPM beta can be obtained.

[5] Another possibility is that estimation risk is not "priced" since this risk can be diversified away, especially in a market with many securities. See Banz (1981), Reinganum and Smith (1983), and Lambert et al. (2007). On the other hand, Easley and O'Hara (2004) as well as the papers cited in the paragraph discuss the possibility of non-diversifiable estimation risk even in a market with many securities.

[6] Lambert et al. (2007) describe this feature as the "assessed covariances" affecting equilibrium prices while "the firms' real decisions are being held constant.

This setup is comparable to that of Clarkson and Thompson (1990). Our setup is simpler as we consider a one-period economy. Clarkson and Thompson (1990) adopted a multi-period setup as they wanted to make the process of information accumulation more explicit and, in their model, the number of periods is tied to the amount of information. In our case, the number of periods is not tied to the amount of information. Rather, the amount of information is determined by the number of analysts following each stock in any given period.

2.2. Estimation risk and the predictive distribution

We assume that the agent knows the true mean of the dividend amount of stock j, v_j, as well as the true value ω. That is, the mean dividend amount of stock i, v_i, is the only parameter whose value is unknown to the agent. For the value of v_i, the agent makes inferences from the information generated by analysts. The number of analysts following stock i is N. Suppose that each analyst makes a random draw from $N(v_i, \omega^2)$ and reports it as a "dividend forecast". Let us denote the forecasts by N analysts as $X_1, \dots, X_N$. The agent adopts a Bayesian approach. That is, he/she combines his/her prior (which we assume to be a diffuse prior) with data and produces the following posterior for v_i:

$$v_i \sim N(\bar{X}, \frac{1}{N}\omega^2) \tag{6}$$

where $\bar{X}$ is the average of $X_1, \dots, X_N$. $\frac{1}{N}$ in the above formula is the indicator of estimation risk. In our setup, if the number of analyst forecasts is large, then estimation risk is small.

Given the posterior for v_i, the posterior for μ_i is determined as

$$\mu_i \sim N\left(\frac{\bar{X}}{P_i} - \frac{1}{P_f}, \frac{1}{N}\frac{1}{P_i^2}\omega^2\right) \tag{7}$$

The predictive distribution for excess returns can be written as

$$R \sim N(\mu^*, \Sigma^*) \tag{8}$$

where

$$\mu^* = \begin{pmatrix} \frac{\bar{X}}{P_i} - \frac{1}{P_f} \\ \mu_j \end{pmatrix} \tag{9}$$

and

$$\Sigma^* = \begin{pmatrix} (1+\frac{1}{N})\frac{1}{P_i^2}\omega^2 & 0 \\ 0 & \frac{1}{P_j^2}\omega^2 \end{pmatrix} \tag{10}$$

2.3. Familiarity and portfolio optimization

We assume that the agent maximizes the mean–variance-familiarity criterion as described by Boyle et al. (2012). In this criterion, consideration of familiarity is modeled via "optimization assuming the worst". More specifically, given the posterior distribution of μ_i in Eq. (7), the agent considers an interval around the posterior mean:

$$\left[\frac{\bar{X}}{P_i} - \frac{1}{P_f} - \alpha_i\sqrt{\frac{1}{N}\frac{1}{P_i^2}\omega^2}, \frac{\bar{X}}{P_i} - \frac{1}{P_f} + \alpha_i\sqrt{\frac{1}{N}\frac{1}{P_i^2}\omega^2}\right] \tag{11}$$

In the above, α_i determines the length of the interval and indicates the aversion toward unfamiliarity, i.e., it represents how unfamiliar the agent feels toward stock i. Then the agent replaces the predictive means μ^* with smaller numbers μ^{**} based on the lower end of the interval above:

$$\mu^{**} = \mu^* - \begin{pmatrix} \alpha_i\sqrt{\frac{1}{N}\frac{1}{P_i^2}\omega^2} \\ 0 \end{pmatrix} \tag{12}$$

where μ^{**} can be interpreted as the worst-case mean excess return. As we assume full knowledge regarding stock j, we assume that the agent is fully familiar with stock j, and no adjustment for the familiarity effect is introduced.

To write down the agent's optimization problem, let $w = \begin{pmatrix} w_1 & w_2 \end{pmatrix}'$ be the vector of stock weights. We assume that the agent's wealth is \$1. Thus, w_1 and w_2 represent dollar holdings of the two stocks. The dollar holding of the risk-free bond is $1 - w_1 - w_2$. Then the agent's solves the following

$$\max_w w'\mu^{**} - \frac{1}{2}\gamma w'\Sigma^* w \tag{13}$$

subject to Eq. (12), where γ is a risk aversion parameter, μ^{**} reflects the familiarity effect, and estimation risk is represented by Σ^*, which is distinct from the familiarity effect represented by μ^{**}.

The first order condition of the optimization problem can be written as

$$w = \frac{1}{\gamma}(\Sigma^*)^{-1}\mu^{**} \tag{14}$$

The agent's optimal holding of the risk-free bond is $1 - w_1 - w_2$.

2.4. Equilibrium and CAPM beta

In equilibrium, the agent's optimal holding should equal the supply. Thus, we have the following three equilibrium conditions:

$$\begin{pmatrix} P_i \\ P_j \end{pmatrix} = \frac{1}{\gamma}(\Sigma^*)^{-1}\mu^{**}$$
$$0 = 1 - P_i - P_j \tag{15}$$

Substituting the formula for Σ^* and μ^{**} in Eqs. (10) and (12), the equilibrium condition becomes

$$\begin{aligned} P_i &= \frac{\bar{X} - \alpha_i\sqrt{\frac{1}{N}\omega^2} - \gamma(1+\frac{1}{N})\omega^2}{\bar{X} - \alpha_i\sqrt{\frac{1}{N}\omega^2} - \gamma(1+\frac{1}{N})\omega^2 + v_j - \gamma\omega^2} \\ P_j &= \frac{v_j - \gamma\omega^2}{\bar{X} - \alpha_i\sqrt{\frac{1}{N}\omega^2} - \gamma(1+\frac{1}{N})\omega^2 + v_j - \gamma\omega^2} \\ P_f &= \frac{1}{\bar{X} - \alpha_i\sqrt{\frac{1}{N}\omega^2} - \gamma(1+\frac{1}{N})\omega^2 + v_j - \gamma\omega^2} \end{aligned} \tag{16}$$

From the formula above, it is easy to confirm $P_i < P_j$. Note that

$$P_i - P_j = \frac{(\bar{X} - v_j) - \frac{1}{N}\gamma\omega^2 - \alpha_i\sqrt{\frac{1}{N}\omega^2}}{\bar{X} - \alpha_i\sqrt{\frac{1}{N}\omega^2} - \gamma(1+\frac{1}{N})\omega^2 + v_j - \gamma\omega^2} \tag{17}$$

The numerator of the above formula has three components. The first component $\bar{X} - v_j$ has the mean of $v_i - v_j$. As this component has nothing to do with estimation risk and the unfamiliarity premium, we may ignore it (i.e., we may assume that $v_i = v_j$). The second component $-\frac{1}{N}\gamma\omega^2$ represents estimation risk. Larger estimation risk in stock i makes P_i smaller than P_j. The third component $-\alpha_i\sqrt{\frac{1}{N}\omega^2}$ represents the unfamiliarity premium. When the agent feels unfamiliar toward stock i, P_i becomes smaller than P_j.

We now turn to CAPM beta. Given the weights of two stocks and the true distribution of excess returns in Eq. (3), the CAPM beta of stock i is determined as follows:

$$\beta_i = \frac{\mathrm{Cov}\left(R_i, \frac{P_i}{P_i+P_j}R_i + \frac{P_j}{P_i+P_j}R_j\right)}{\mathrm{Var}\left(\frac{P_i}{P_i+P_j}R_i + \frac{P_j}{P_i+P_j}R_j\right)} = \frac{1}{2P_i} \tag{18}$$

Similarly, for stock j,

$$\beta_j = \frac{1}{2P_j} \tag{19}$$

Thus,

$$\beta_i - \beta_j = \frac{1}{2P_iP_j}(P_j - P_i) \tag{20}$$

Since $P_i < P_j$, we thus confirm $\beta_i > \beta_j$. The difference between these two beta's is determined by the same two factors highlighted in Eq. (17), i.e., the estimation risk component $-\frac{1}{N}\gamma\omega^2$ and the unfamiliarity component $-\alpha_i\sqrt{\frac{1}{N}\omega^2}$. This analysis implies that if investors feel more familiar toward an old firm, its price will be higher and its beta will be lower. This effect is distinct from the estimation risk consideration, i.e., whether more information is generated for the old firm.

3. Data and variables

3.1. Data

The sample used in this study includes all common stocks that were traded on the NYSE, AMEX, and NASDAQ at the time of portfolio formation from the beginning of 1966 to the end of 2016. We exclude companies from the financial sector[7] and also those stocks whose month-end prices are below \$1. Furthermore, to be included in the analysis for year t, a stock needs to have at least 27 weekly returns between July of year $t-1$ and June of year t. This is to ensure that we can estimate the beta of every stock as of the end of June of each year. We use the Thursday-to-Wednesday return as our weekly return. For our baseline analysis, we exclude stocks whose age (i.e., the number of years since the founding and/or incorporation date) is greater than 100 years. The data cover the period from July 1966 to June 2016. We calculate our key variables for the end of June of each year from three data sources: CRSP, Compustat, and IBES.

[7] In CRSP, the codes for shares, shrcd, was 10 or 11, the exchange codes, exchcd, were 1, 2, or 3, and we excluded SIC codes, siccd, from 6000–6099.

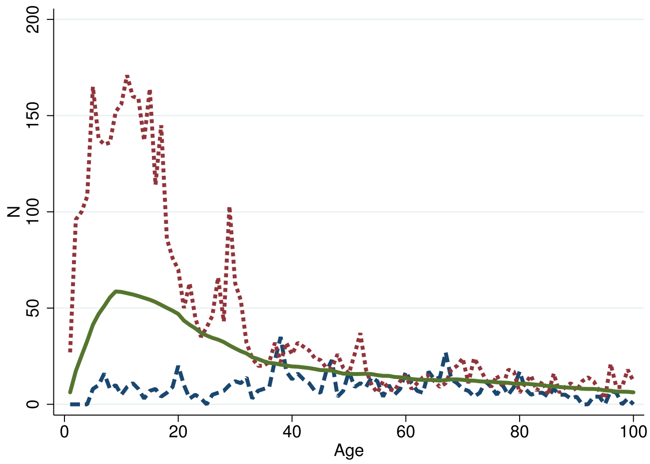

Fig. 1. Age distribution of the sample data. *Note*: The initial sample includes stock-years of non-financial common stocks in the CRSP-Compustat universe, of the period between 1966 and 2016, and of ages between 1 and 100. We have determined the age as the number of years (as of the end of June of year t) since incorporation or founding, whichever is earlier. We have counted the number of firms in each age–year combination (a, t). The short-dashed line represents these numbers for year 1998 when the sample size is the largest. The long-dashed line represents these numbers for year 1968 when the sample size is the smallest. The solid line represents the average across years of these numbers.

3.2. Beta measure

Our beta is estimated from weekly returns in excess of the risk-free rate.[8] For year t, beta is based on weekly excess returns from July of year $t-1$ to June of year t. To mitigate microstructure noise that may affect the beta estimates, we follow Han and Lesmond (2011) and use the midpoint of the bid–ask spread to measure prices and consequently returns. Additionally, in order to control for nonsynchronous trading, we adopt Dimson's (1979) technique and include the lagged market excess returns as regressors so that our regression equation is

$$r_t = \alpha + \beta_1 r_{M,t} + \beta_2 r_{M,t-1} + \beta_3 \frac{r_{M,t-2} + r_{M,t-3} + r_{M,t-4}}{3} + \epsilon_t \tag{21}$$

where $r_{M,t}$ is the market excess return. Our beta estimate is the sum of three coefficient estimates, i.e., $\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$.

3.3. Age measure

Our measure of age is based on the earliest available date of incorporation or founding date of the companies. To construct our age variables, we used the data collected by Jovanovic and Rousseau (2001) on incorporation and founding dates and the Ritter dataset on founding dates.[9] Our age variable is the number of years since the founding and/or incorporation date as of June of year t.

Our sample begins in 1966 and we consider ages of companies from 1 to 100 years old in every given year. Fig. 1 shows the distribution of companies over age in our sample. The short-dashed line represents the number of firms in the age cohort for the year 1998 when the sample size is the largest. The long-dashed line represents the number of firms in the age cohort for the year 1968, when the sample size is the smallest. The solid line represents the average across all years. For example, in 1998, there were 165 companies that were five years old and twelve companies that were 100 years old. In 1968, there were eight companies that were five years old and zero companies that were 100 years old.

3.4. Fundamental measures

Beaver et al. (1970) were the first to document the importance of using accounting measures to explain beta. Accordingly, in this paper we consider several fundamental measures including the main variables used by Beaver et al. (1970). Specifically, we

[8] It is important to use high-frequency returns data because the accuracy of covariance estimation improves with the sample frequency (Merton, 1980). However, with high frequency microstructure issues become relevant. For example, Lo and MacKinlay (1990) show that due to nonsynchronous trading small stocks tend to react with a delay to common news. Furthermore, Gilbert et al. (2014) highlight potential mispricing driven by the use of daily frequency in constructing betas. The weekly frequency is a good compromise to ensure we have sufficiently high frequency data while simultaneously mitigating nonsynchronous trading or bid–ask bounce effects (see, among others, Lim (2001) and Zhang (2006)). As a robustness check, we also computed betas using daily returns instead of weekly returns. We find that the main results of the paper are confirmed.

[9] This data was obtained from https://site.warrington.ufl.edu/ritter/files/2016/09/FoundingDates.pdf and was used in Field and Karpoff (2002) and Loughran and Ritter (2004). In another analysis not reported in this paper, we also used the IPO date as a proxy for age and find similar qualitative results. Fink et al. (2010) advocate the use of the date of incorporation/founding as a more accurate proxy for age rather than the IPO date.

consider size, book-to-market ratio, leverage, and the payout ratio. Our measure of size is the logarithm of the market capitalization as of June of year t. We calculate book equity following Fama and French (1993); it is the sum of the book value of stockholders' equity and balance-sheet deferred taxes, minus the book value of preferred stock. If investment tax credit is available, it is added to the book value. For the book value of preferred stocks, we use the redemption, liquidation, or par value. The book-to-market (BM) is the ratio of the book value of the last fiscal year as of the end of June of year t divided by the market capitalization at the end of June of year t. Leverage is calculated as book equity divided by total liabilities plus one (i.e., leverage = $\frac{BV}{TL} + 1$). The payout ratio is calculated as the dividends paid during the last fiscal year over the net income of the last fiscal year.

We also compute two indicators of the variabilities of earnings. The first is earnings standard deviation, which is computed from the earnings-to-price ratios of the 12 quarters ending on or before the end of July of each year. The second is earning covariability, which is computed as the coefficient estimate in the regression of the earnings-to-price ratio of a stock on the market earnings-to-price ratio.

3.5. Liquidity measures

It is reasonable to think that the liquidity of a stock improves as the firm matures and grows. One may wonder if these changes in liquidity could cause the decline in beta. Indeed, liquidity is considered a determinant of cost of capital (e.g., Amihud and Mendelson (2000)) and a priced state variable (e.g., Pastor and Stambaugh (2003)). Jacoby et al. (2000) derive a liquidity-adjusted version of the CAPM and demonstrate that the measure of systematic risk should incorporate liquidity costs. Therefore, we include the bid–ask spread as a measure of liquidity and the liquidity beta, which captures the exposure to a liquidity factor. The liquidity beta is the coefficient estimate obtained from the regression of weekly (Thursday-to-Wednesday) returns of the stock on the weekly average of daily innovation in market liquidity using the one-year data from July of year $t-1$ to June of year t. Daily innovation in market liquidity is calculated in four steps. First, daily illiquidity of individual stocks is calculated as the ratio of the daily return to the daily dollar trading volume (Amihud, 2002). Second, market illiquidity is calculated as the value-weighted average of the one-day change in illiquidity of individual stocks. Third, innovation in market illiquidity is determined as the residual from an AR(2) regression of market illiquidity, using the one-year data from July of year $t-1$ to June of year t. Finally, innovation is standardized by dividing it by the standard deviation and multiplying by -1.

3.6. Life-cycle proxies

We construct four proxies for life-cycle stages. The first proxy is from Dickinson (2011). Dickinson (2011) provides a measure (DCS) for the life cycle based on cash flow patterns from operations, investing, and financing activities. In particular, the author categorizes firms into one of five stages: introduction, growth, maturity, shake-out, and decline. For example, firms in the introduction stage are associated with negative cash flows from operations, negative cash flows from investing activities, and positive cash flows from financing activities. The second proxy is from DeAngelo et al. (2006). DeAngelo et al. (2006) suggest the use of ratio of retained earnings to total assets (RETA) as a measure of life cycle. The third and fourth proxies are from Faff et al. (2016). The third proxy is obtained using a multiclass linear discriminant analysis (MLDA). In particular, Faff et al. (2016) first classify firms into different groups using Dickinson's (2011) stages and then perform a linear discriminant analysis by regressing the group variable on age, RETA, EBIT, and asset growth.[10] The last proxy uses the age of the firm but adjusted for industry and size effects. The adjustment is obtained by regressing age on industry and size dummies and then using the percentile rank of the residual value as a proxy of the life cycle. Different from Faff et al. (2016), we use the age from incorporation/founding date rather than age from listing date.

3.7. Information measures

We use several proxies to measure the amount and the heterogeneity of the information. A commonly used measure is the number of analysts following a company. Hence, each month, we determine the number of analysts covering each company from the IBES monthly files, which start in 1982. We then take the average of this number from July of year $t-1$ to June of year t. We also use the dispersion of analyst forecasts. Accordingly, each month, we determine the dispersion as the standard deviation of forecasts over the monthly average of daily closing price. We divide by price to normalize the effect of companies with different size. The forecasts are for the nearest fiscal year earnings-per-share (EPS). We then take the average of monthly dispersion from July of year $t-1$ to June of year t.

We also use measures of public and private information on a particular company. For the precision of public information, we follow Botosan et al. (2004). It is $\frac{SE-D/N}{(SE-D/N+D)^2}$, where SE is the squared error in the mean forecast, D is the forecast dispersion (measured in variance), N is the number of forecasts. The forecasts are the last forecasts for quarterly EPS. For the precision of private information, we also follow Botosan et al. (2004). It is $\frac{D}{(SE-D/N+D)^2}$. Like Botosan et al. (2004) we adjust the data as follows: if the number of analysts is less than three, we set the variables to missing; if either the private or public information measure is negative, we set both variables to missing; in any given year, these variables need to have valid values for at least three quarters and we choose the median value of the last three or four quarters depending on what is available. We make an additional modification and divide both D and SE by the mean of their estimates. Based upon these two measures, we can compute the precision of total information as the sum of the precision of public information and the precision of private information. We also calculate the share of public information on a given security as the precision of public information divided by the precision of total information.

[10] Following Faff et al. (2016) we merge the shake-out and decline stage in Dickinson's (2011) measure.

Table 1
Summary statistics.

Variable	Obs	Mean	SD	Min	Median	Max
Beta	114 635	1.34	1.53	−20.14	1.22	21.44
Age	114 635	33.89	25.48	1	26	100
Market cap	114 635	1390.81	8863.48	0.59	140.20	715 599.81
B/M	113 679	0.76	0.65	0.02	0.58	5.27
Leverage	114 117	2.37	2.13	1	1.82	30.06
Payout ratio	85 351	0.23	0.43	0	0.05	5.75
Earnings variability	87 493	0.03	0.05	0.0002	0.02	0.53
Earnings covariability	87 107	1.08	6.17	−33.58	0.39	53.51
Liquidity beta	113 529	0.01	0.17	−1.59	0.001	1.72
Bid–ask spread	114 407	0.03	0.03	0.0001	0.02	0.21
Number of analysts	70 873	4.42	4.86	0	2.67	26.83
Dispersion	56 641	0.01	0.03	0	0.004	0.61
Public info	17 792	0.01	0.02	0	0.002	0.17
Private info	17 781	0.01	0.02	0	0.001	0.29
Public info share	17 839	0.64	0.26	0	0.69	1

Note: The initial sample includes stock-years of non-financial common stocks in the CRSP-Compustat universe for the period between 1966 and 2016 and for ages between 1 and 100. **Beta** is calculated as the sum of three coefficient estimates obtained from the regression of weekly (Thursday-to-Wednesday) returns of the stock on the market return (of week w), one week lagged market return (i.e., of week $w-1$), and the market return from week $w-4$ to week $w-2$, using the one-year data from July of year $t-1$ to June of year t. Stock returns are based on mid prices rather than closing prices whenever possible, to mitigate the impact of bid–ask spread. **Age** is determined as the number of years (as of the end of June of year t) since incorporation or founding, whichever is earlier. **Market cap** is the market capitalization in million dollars as of June of year t. **B/M** is the ratio of the book value – of the last fiscal year whose statement is available as of the end of June of year t – divided by the market capitalization of the end of June of year t. We calculate book equity as the sum of the book value of stockholders' equity and balance-sheet deferred taxes, minus the book value of preferred stock. If investment tax credit is available, it is added to the book value. For the book value of preferred stock, we use the redemption, liquidation, or par value. **Leverage** is calculated as book equity divided by total liabilities plus one. **Payout ratio** is calculated as the dividends paid during the last fiscal year over the net income of that fiscal year. **Earnings variability** is the standard deviation of the earnings-to-price ratios of the 12 quarters ending on or before July of year t. Earnings are quarterly earnings, and the price is the beginning-of-the-quarter price. If the earnings-to-price ratios are available for less than 10 quarters, this variable is set to missing. **Earnings covariability** is the coefficient estimate in the regression of the earnings-to-price ratio of a stock on the market earnings-to-price ratio. The market earnings-to-price ratio is the value-weighted average of individual stocks' earnings-to-price ratios. The regression is based on the 12 quarters ending on or before July of year t. **Liquidity beta** is the coefficient estimate obtained from the regression of weekly (Thursday-to-Wednesday) returns of the stock on the weekly average of daily innovation in market liquidity using the one-year data from July of year $t-1$ to June of year t. Daily innovation in market liquidity is calculated in four steps. First, daily illiquidity of individual stocks is calculated as the ratio of the daily return to the daily dollar trading volume. Second, market illiquidity is calculated as the value-weighted average of the one-day change in illiquidity of individual stocks. Third, innovation in market illiquidity is determined as the residual from AR(2) regression of market illiquidity, using the one-year data from July of year $t-1$ to June of year t. Finally, innovation is standardized by dividing it by the standard deviation, and is multiplied by −1. **Bid–ask spread** is the average of daily bid–ask spread for the one year period from July of year $t-1$ to June of year t. **Number of analysts** is the average number of analysts covering each company, as reported in the IBES monthly files, between July of year $t-1$ and June of year t. **Dispersion** is the average of monthly dispersion for July of year $t-1$ to June of year t, where monthly dispersion is determined as the standard deviation of analyst forecasts over the share price. Only the forecasts for the nearest fiscal year earnings-per-share (EPS) are used. Precision of public information (**Public info**) and Precision of private information (**Private info**) are the medians of the quarterly precisions, where the quarterly precisions are calculated as $(SE-D/N)/(SE-D/N+D)^2$ and $D/(SE-D/N+D)^2$, where SE is the squared error in the mean forecast divided by the mean forecast, D is the variance of forecasts divided by the mean forecast, and N is the number of forecasts. The latest available forecasts for quarterly EPS are used. If the number of analysts is less than three, then the quarterly precision is set to missing. If the less than three quarterly precisions are available, we set the variable to missing. If either the private or public information variable is negative, we set both variables to missing. **Public info share** is calculated as public info/(public info + private info).

3.8. Summary statistics

Table 1 reports the summary statistics for our key variables.[11] We average the data over time and cross-sectionally. For the entire sample period, the mean beta is 1.34 and the average company is 33.89 years old.[12] The average company size is 1.39 billion dollars, the average book-to-market ratio is 0.76, the average leverage of the companies is 2.37, the average payout ratio is 23%, the earnings variability is 0.03, and the average earnings covariability is 1.08. The average illiquidity beta is 0.01. The average number of analysts following a stock is 4.42, the dispersion of analyst forecasts is 1%, and public and private information have similar average values.

[11] Fundamental variables were trimmed. The extreme 1% of the values were removed. For each variable, we determined whether trimming-at-the-left as well as trimming-at-the-right was necessary. If there was a natural lower bound (e.g., leverage of 1, bid–ask spread of 0, etc.), we applied trimming at the right only. When trimming was applied to both the left and right sides of the distribution, 0.5% was removed from each side. The critical values for the trimming were selected from the entire sample, not from each year. We chose to trim values in this way because we felt that extreme values are probably errors (not because extreme values are just extreme). We applied left and right trimming to liquidity beta, B/M, earnings yield, earnings covariability. We applied right trimming only to bid–ask spared, leverage, payout ratio, earnings standard deviation, number of analysts, dispersion, public info, and private info. We did not trim public info share, age, beta, or returns.

[12] Note that the average beta is higher than that reported by some other studies (e.g., Gilbert et al. (2014)). This is due to Dimson's adjustment. Without this adjustment, the average beta is 0.96. Hollstein and Prokopczuk (2016), Hollstein et al. (2019) and Hollstein et al. argue against the Dimson's adjustment for higher frequency returns in the beta calculation. Our main results are robust even if we use the betas computed without the Dimson's adjustment. These results are available in the Internet Appendix.

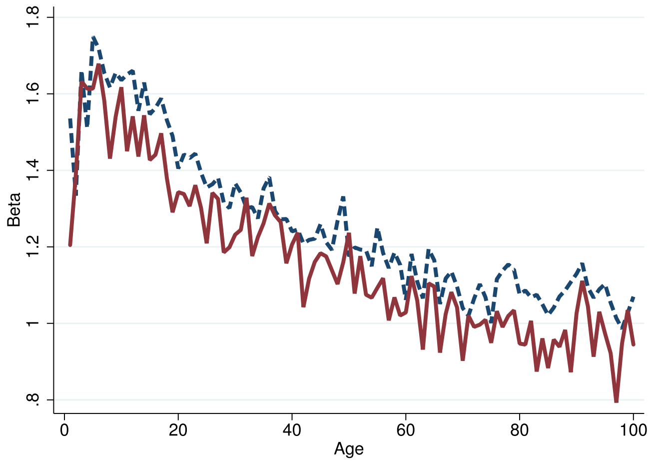

Fig. 2. The decline of beta with Age *Note*: The figure plots beta against age. The solid line represents value-weighted beta, and the dotted line equal-weighted beta. The initial sample includes stock-years of non-financial common stocks in the CRSP-Compustat universe for the period between 1966 and 2016 and for ages between 1 and 100. We have determined the age as the number of years (as of the end of June of year t) since incorporation or founding, whichever is earlier. We have sorted the stock-years of year t into 100 age portfolios corresponding to ages between 1 and 100; i.e., portfolio (t, a) includes stock-years of year t and age a. For each portfolio, we have calculated value-weighted and equal-weighted beta out of individual stock betas. Individual stock betas are estimated from weekly returns between July of year $t-1$ and June of year t. We then take the average of these values across years holding age fixed.

Fig. 2 shows the decline of beta over firm age. We computed equal-weighted and value-weighted portfolio betas for age-sorted portfolios. In the first few years, due to the small number of stocks in the portfolios the beta pattern is not clear, but after that beta declines from the peak of around 1.7 down to around 1.0. Fig. 3 shows how our key variables change over firm age. Many of the variables exhibit noticeable patterns over firm age. For example, more analysts follow companies over time. We also find that with age, companies become larger, they have less leverage, and they have higher book-to-market ratios. Despite these trends, we show that these variables are inadequate to explain beta–age relationship.

4. Empirical analysis

4.1. Methodology

To study the effect of age on beta, we run a regression of beta on age and several other factors:

$$\beta_{i,t} = \gamma_0 + \gamma_1 a_{i,t} + \gamma_2 \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{22}$$

We perform three sets of regression analyses: one is performed at the stock level and the other two are performed after age-sorted portfolio construction. Hence, γ_1 represents the relationship between the age of the stock (or portfolio of companies) and the stock's beta (or portfolio's average beta), and γ_2 represents the coefficients on a set of explanatory variables, $\mathbf{X}$. For the stock-level analysis, we present panel estimates adjusting standard errors for possible within-firm correlation of errors.

For the portfolio analysis, between 1966 and 2016, we classify stocks by their age in every year creating age cohorts. Thus, a stock that is founded or incorporated between July 1, 1970 and June 30, 1971 is part of the 1970 cohort. Its age in any subsequent year would be that year minus its incorporation/founding date. Due to the rich source of data, we create 101 age-cohort portfolios (Age 0 to Age 100) for every year. We then drop the age 0 cohort from our analysis since many stocks enter the database only after age 1. We use the age of stocks in conjunction with other variables to understand the effects of age on beta. Next, we construct a beta for each age cohort. Thus, we first estimate the beta of each individual stock in our database for each year as described in Section 3.2. We then calculate the age-cohort portfolio beta as the equal-weighted or market-cap weighted average of all stocks in each age–portfolio as of July 1.

At the portfolio level, we use two regression methodologies to understand the effect of age on beta. The first is a pooled cross-sectional time-series regression, whereby we take all observations from every year in our sample with betas and corresponding independent variables and run one regression. We also compute double-clustered standard errors in the spirit of Petersen (2009) to avoid biased estimates of the standard errors that can arise from using persistent variables. The second approach is to estimate Fama–MacBeth regressions. Each year we run a cross-sectional regression; we estimate the parameters and then average them across all years.

4.2. Age, fundamentals, and beta

To untangle the different sources influencing beta, we consider several specifications of our regression equations. Table 2 reports the stock level regression results where betas are regressed against age and other factors. Column (1) shows a simple regression of

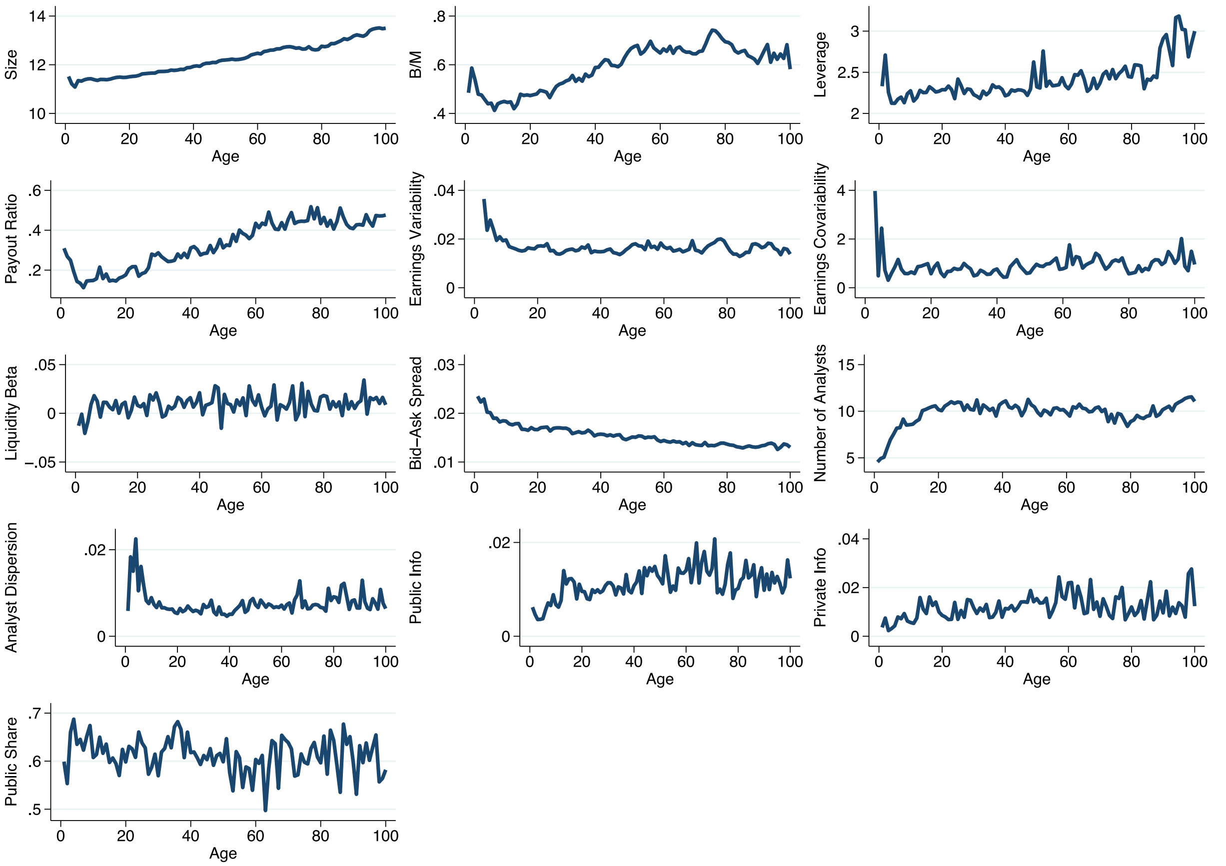

Fig. 3. Other variables with age. *Note*: The figure plots size and other variables against age. See the notes to Table 1 for a description of each variable. The initial sample includes stock-years of non-financial common stocks in the CRSP-Compustat universe for the period between 1966 and 2016 and for ages between 1 and 100. We have determined the age as the number of years (as of the end of June of year t) since incorporation or founding, whichever is earlier. We have sorted the stock-years of year t into 100 age portfolios corresponding to ages between 1 and 100; i.e., portfolio (t, a) includes stock-years of year t and age a. For each portfolio, we have calculated the equal-weighted average of each variable. We then take the average of these values across years holding age fixed.

beta against age. Column (2) shows the effect of age and size on beta. Column (3) shows the effect of age on beta while controlling for many other factors, including fundamental variables, leverage, and illiquidity proxies.

In all estimations, average portfolio beta declines with age. The coefficient γ_1 is between −0.004 and −0.007. A value of −0.007 implies that for every 10 years of life, the portfolio beta declines by 0.07 points. For a company with an initial beta of 1.40, this amounts to a 10% decline over twenty years. This decline corresponds to the pattern shown earlier in Fig. 2. In the figure, beta steadily declines from year 5 to year 100 from 1.74 to 1.06 for the equal-weighted portfolio.[13] Payout ratio and earnings variability are the only other variables significant in determining the beta of a company. Variability in earnings is a potential indicator of the systematic risk component of a company's future earnings. Payout ratio, as suggested by Beaver et al. (1970), can also be viewed as a proxy for management's perception of the systematic risk associated with the firm's earnings. A significant correlation between beta and earnings variability and payout ratio was also documented by Beaver et al. (1970).

We note that the magnitude on the age coefficient is reduced when the other variables are included, consistent with some of the fundamental factors capturing some information effects included in the age variable.[14] However, these fundamental factors are unable to fully capture the effect of the declining beta with age. The coefficient on age remains significant across different specifications. Hence, age seems to be a very important and novel factor determining beta.

Table 3 reports the portfolio-level pooled regression results. In this case, more variables such as size, book-to-market ratio, and earning covariability are significant explanatory variables of beta. Nevertheless, age remains a significant determinant of beta.

In Table 4, we also show the Fama–MacBeth results for beta on age. The results shown in Table 3 are confirmed. Despite that each cross-sectional regression is based only on 100 observations, age remains significant even when we include all the control variables.

[13] This represents a coefficient closer to −0.007.

[14] For example the size of the firm has also been considered a proxy for quantity of information (e.g., Clarkson and Satterly, 1997).

Table 2
Age, fundamentals, and beta: Stock-level regressions.

	(1)	(2)	(3)
Age	−0.007 (−6.16) ***	−0.006 (−5.70) ***	−0.004 (−4.97) ***
Size		−0.012 (−0.88)	−0.002 (−0.12)
B/M			−0.008 (−0.24)
Leverage			0.002 (0.29)
Payout ratio			−0.190 (−9.27)
Earnings variability			1.643 (5.14) ***
Earnings covariability			0.003 (1.65)
Liquidity beta			−0.082 (−0.75)
Bid–ask spread			−2.241 (−1.46)
N ∗ T	114,635	114,635	113,309
Adj R sq	0.012	0.012	0.028

Note: The table reports on the regressions of beta on age and other variables of individual stocks. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. See the notes to Table 1 for description of each variable. The estimation includes a constant term and dummy variables indicating whether each variable – other than beta, age, market cap, and B/M – is missing. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

4.2.1. Further analysis regarding leverage

Basic fundamental factors are insufficient to explain the decline in beta with age. In our previous analyses, we measured the beta of each company and then created weighted average betas for the portfolio of stocks in each age cohort. However, the corporate finance literature recognizes that the equity beta of a firm differs depending on the financial leverage of the company (i.e., debt-to-equity ratio). Although we already used leverage as an explanatory variable in the regressions, for robustness we also compute the unlevered beta of each company and repeat our earlier analysis.

In particular, we take all the companies in our sample and each period, we adjust the beta by unlevering it in the following way.

$$\beta_u = \beta_t \frac{(1 + L_t)}{(1 + L_{t-1})} \tag{23}$$

where β_u is our measure of unlevered beta, β_t is the unadjusted or levered beta which is measured from historical stock return data, L_t is the most recent leverage ratio of the company (i.e., debt-to-equity ratio at time of portfolio formation), and L_{t-1} is the leverage ratio as of the end-December of year $t-1$.[15] Because of data errors, we winsorize all values of $\frac{(1+L_t)}{(1+L_{t-1})}$ to be between 0.5 and 2. If we cannot calculate this ratio due to missing data, we use the value 1.

Table 5 reports the same regressions discussed earlier on un-levered beta. We find that none of our qualitative results changes. The coefficient on age is remarkably robust to these changes and age is statistically significant in explaining beta.

4.2.2. Further robustness checks

We run additional analyses to establish the robustness of our finding. To save space we report only one table in the main paper and report the other tables in a separate internet appendix.

First, we control for additional beta determinants. Cosemans et al. (2016) use operating leverage and momentum as determinants of beta (see also Grundy and Martin (2001) for the link between momentum and beta). In addition, Cosemans et al. (2016) use

[15] Our beta is measured from July to June data, thus, L_{t-1} is set to be the leverage as of the end of December of year $t-1$, while L_t is measured as of the end of June of year t. Both leverage ratios are calculated as the weighted average of two leverage ratios reported at nearby fiscal year-end dates. For stocks whose fiscal year ends in December, we take the exact leverage ratio, not a weighted average, for L_{t-1}, and for stocks whose fiscal year ends in June, we take the exact leverage ratio, not a weighted average, for L_t.

Table 3
Age, fundamentals, and beta: Portfolio-level regressions.

	(1)	(2)	(3)
Age	−0.007 (−10.68) ***	−0.006 (−7.03) ***	−0.004 (−5.93) ***
Size		−0.041 (−2.14) **	−0.045 (−3.41) ***
B/M			−0.141 (−2.27) **
Leverage			0.008 (0.76)
Payout ratio			−0.281 (−5.82) ***
Earnings variability			3.529 (4.35) ***
Earnings covariability			0.018 (3.25) ***
Liquidity beta			0.070 (0.83)
Bid–ask spread			2.455 (1.01)
N ∗ T	4964	4964	4964
Adj R sq	0.120	0.126	0.169

Note: The table reports on the regressions of beta on age and other variables of year–age portfolios. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. We have sorted the stock-years of year t into 100 age portfolios corresponding to ages between 1 and 100; i.e., portfolio (t, a) includes stock-years of year t and age a. For each year–age portfolio, we have calculated beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, and bid–ask spread. Except for size, which is the equal-weighted average of individual stocks' size, all the other variables are the value-weighted average of the corresponding variables of individual stocks. See the notes to Table 1 for description of each variable. The estimation includes a constant term and dummy variables indicating whether each variable–other than beta, age, market cap, and B/M–is missing. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

industry dummy variables. Table 6 show that results are similar if we include operating leverage and momentum and we control for industries using industry dummies.[16]

Second, we repeat our portfolio regressions replacing value-weighted beta with equal-weighted beta, and find that the results are comparable (see Table A4 in the internet appendix).

Third, we include the squared age term to account for possibly non-linear relationship between beta and age. The squared age term turns out to be significant, but its magnitude is small enough to justify its omission (see Tables A5 and A6 in the internet appendix.) As an alternative, we tried to include the natural logarithm of age in the regressions and find that age in logs remains significant (see Table A12 in the internet appendix.)

Fourth, to have better understanding of possible non-linearity, we have repeated the regression analysis for the sub-sample of young firms and also for the sub-sample of old firms. We exclude stock-years whose age is less than 10 since the number of observations for these ages is small and the estimation seems unstable. We then split the remaining sample into two: the first for the age up to 30 and the second for the age over 31. We find that the effect of age on beta is stronger for young firms (age up to 30). The coefficient for young firms is up to 5 times larger than the coefficient for old firms (see Tables A7, A8, A9, and A10 in the internet appendix).

Lastly, to address a potential impact on the results of firms leaving the sample, we repeat the analysis for a balanced sub-sample that includes only firms with a complete history between age 10 and age 30 and find that the results are robust (see Table A11

[16] We follow Cosemans et al. (2016) and compute operating leverage as the three-year moving average of the ratio of the percentage change in operating income before depreciation to the percentage change in sales. Momentum is measured as the cumulative return over the 12 months prior to the current month. We also create 12, 38, and 48 industry dummies based on the industry classification from Kenneth French's website.

Table 4
Age, fundamentals, and beta: Portfolio-level Fama–MacBeth regressions.

	(1)	(2)	(3)
Age	−0.007 (−11.86) ***	−0.005 (−8.19) ***	−0.002 (−3.50) ***
Size		−0.068 (−4.11) ***	−0.032 (−2.25) **
B/M			−0.156 (−2.52) **
Leverage			−0.022 (−1.71) *
Payout ratio			−0.323 (−6.77) ***
Earnings variability			3.609 (4.62) ***
Earnings covariability			0.016 (3.24) ***
Liquidity beta			−2.020 (−1.14)
Bid–ask spread			44.845 (2.47) **
N ∗ T	4964	4964	4964

Note: The table reports on the regressions of beta on age and size of year–age portfolios. We carry out Fama–MacBeth estimation. In the first step, we run the regression for each year, and collect the coefficient estimate. In the second step, we calculate the average of the first-step estimates and determine the t-statistics from them. We have sorted the stock-years of year t into 100 age portfolios corresponding to ages between 1 and 100; i.e., portfolio (t, a) includes stock-years of year t and age a. For each year–age portfolio, we have calculated value-weighted beta and equal-weighted size out of individual stocks' beta and size. See the notes to Table 1 for description of each variable. The table reports the coefficient estimates and t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

in the internet appendix).[17] We also perform the analysis using the log of age rather than age and construct 20 portfolios with approximately the same number of stocks instead of the 101 age portfolios. We then verified that the main results were robust (see Tables A12 and A13 in the internet appendix).

4.3. Life-cycle stages and beta

Another explanation of the decline of beta over age is related to different stages of business development that a corporation experiences over its life. These stages are formalized in the life-cycle literature, which has documented that dividend policy (e.g., DeAngelo et al. (2006)), seasoned equity offerings (DeAngelo et al., 2010), cash flow patterns (Dickinson, 2011), and corporate investment and financing policies (Faff et al., 2016) are related to a firm's life-cycle phase.

We use four life-cycle proxies as explained in the data section, and examine whether these proxies help to explain beta. Table 7 presents regression results where we include the four alternative life-cycle proxies. The sample is from 1966 to 2016, with the exception of the DCS measure that starts in 1988 given the limited availability of the cash flow variables.[18] For each life-cycle proxy we present two different regression specifications. The first specification includes only size as a control variable whereas the second specification includes a larger set of control variables. In both specifications there is evidence of a U-shaped pattern when we consider MLDA and DCS: beta declines in the first three stages (introduction, growth, and maturity) but then increases in the last stage (shake-out and decline). Furthermore, age remains significant when these proxies are added to the regression, suggesting that the age effect is distinct from the life-cycle effect. The same is true when we use RETA or the adjusted age as proxies for life-cycle stages.

[17] This result also suggests that the age–beta patterns of long-term survivors and of non-survivors (i.e., firms that get delisted without surviving many years) are not different. Thus, even if CRSP-Compustat database over-represents survivors in the early years creating potential survivorship bias, its impact on our analysis is unlikely to be large.

[18] To compute the MLDA measure we use the DCS measure in the linear discriminant analysis. However, MLDA can still be computed pre-1998 using the estimated regression coefficients from the sample, starting in 1998.

Table 5
Unlevered beta: Portfolio-level regressions.

	(1)	(2)	(3)
Age	−0.007 (−10.26) ***	−0.006 (−7.00) ***	−0.004 (−6.14) ***
Size		−0.036 (−1.85) *	−0.039 (−3.00) ***
B/M			−0.130 (−2.03) **
Leverage			0.004 (0.39)
Payout ratio			−0.284 (−6.04) ***
Earnings variability			3.653 (4.55) ***
Earnings covariability			0.019 (3.44) ***
Liquidity beta			0.055 (0.66)
Bid–ask spread			2.379 (0.97)
N ∗ T	4964	4964	4964
Adj R sq	0.118	0.122	0.163

Note: The table reports on the regressions of unlevered beta on age and other variables of year–age portfolios. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. We have sorted the stock-years of year t into 100 age portfolios corresponding to ages between 1 and 100; i.e., portfolio (t, a) includes stock-years of year t and age a. For each year–age portfolio, we have calculated unlevered beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, and bid–ask spread. Except for size, which is the equal-weighted average of individual stocks' size, all the other variables are the value-weighted average of the corresponding variables of individual stocks. The unlevered beta of a stock is obtained by multiplying the original beta with $\frac{(1+L_t)}{(1+L_{t-1})}$ where L_t is the most recent leverage (i.e., debt-to-equity) ratio of the company, and L_{t-1} is the leverage ratio as of the end of December of year $t-1$. See the notes to Table 1 for description of all the other variables. The estimation includes a constant term and dummy variables indicating whether each variable–other than beta, age, market cap, and B/M–is missing. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

4.4. Information and beta

In the previous subsections, we showed that an important driver of the decline in beta is age, which is not subsumed by fundamental variables and life-cycle proxies. In this section, we consider information variables. That is, if there is little information on a particular company, this may drive beta higher. As more information becomes available on a company, beta might become lower. Our information variables do not go back to 1966, thus, we study their effect since 1982.

As discussed in the data section, we use the number of analysts and the dispersion of analyst forecasts as our proxies for the amount and heterogeneity of available information on a company. We also use the precision of public and private information from Botosan et al. (2004) to understand their potential influence on the beta of a company. Table 8 shows the stock-level results and Table 9 shows the portfolio-level results. Column (1) shows the results of a regression of beta on age. Column (2) shows the results of a regression of beta on age and size. Column (3) shows the results of a regression on beta on age and other fundamental factors. Column (4) and (5) show the results of regressions of beta on age, fundamentals, and the new information factors. We repeat the previous regression specifications because now the sample starts in 1982.

The earlier results remain qualitatively the same in the period from 1982 to 2016; age still influences beta. Earnings variability and payout ratio continue to have a significant role in explaining beta in both stock and portfolio level regressions. In the portfolio-level regression book-to-market ratio and earning covariability are still significant but size is no longer significant. In an unreported regression, we note that size alone, without age, is significant in determining the beta of a company. Several of the information variables are significant, especially in the stock-level regressions. Despite the additional variables appearing statistically significant

Table 6
Including operating leverage, momentum, and industry dummies: Stock-level regressions.

	(1)	(2)	(3)
Age	−0.003	−0.003	−0.003
	(−5.05)	(−5.04)	(−5.09)
	***	***	***
Size	0.005	0.009	0.008
	(0.31)	(0.61)	(0.52)
B/M	0.042	0.036	0.035
	(1.33)	(1.13)	(1.10)
Leverage	0.011	0.010	0.011
	(2.07)	(1.78)	(2.01)
	**	*	**
Payout ratio	−0.120	−0.121	−0.120
	(−6.39)	(−6.44)	(−6.40)
	***	***	***
Earnings variability	1.456	1.461	1.447
	(4.79)	(4.87)	(4.74)
	***	***	***
Earnings covariability	0.003	0.003	0.003
	(1.56)	(1.54)	(1.61)
Liquidity beta	−0.084	−0.086	−0.085
	(−0.77)	(−0.76)	(−0.76)
Bid–ask spread	−2.307	−2.259	−2.195
	(−1.53)	(−1.52)	(−1.48)
Momentum	0.062	0.059	0.058
	(1.32)	(1.26)	(1.25)
Operating leverage	0.000	0.000	0.000
	(0.01)	(−0.04)	(0.04)
N ∗ T	113,309	113,309	113,309
Adj R sq	0.040	0.041	0.042

Note: The table reports on the regressions of beta on age and other variables of individual stocks. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain *t*-statistics. See the notes to Table 1 for description of each variable. We also include operating leverage (the three-year moving average of the ratio of the percentage change in operating income before depreciation to the percentage change in sales), momentum (the cumulative return over the 12 months prior to the current month), and industry dummies based on the industry classification of Fama and French (1997). In column (1) we use 12 industry dummies, column (2) we use 38 industry dummies, and column (3) we use 48 industry dummies. The estimation includes a constant term and dummy variables indicating whether each variable–other than beta, age, market cap, and B/M–is missing. The table reports the coefficient estimates and double-clustered standard errors-based *t*-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

in a way we would expect, age is still significant. Overall, the story is the same. The age of a company affects its beta, even when controlling for fundamental proxies and information proxies. There is something unique about age.[19]

4.5. Familiarity and beta

As discussed in Sections 2.3 and 2.4, familiarity is another factor that can explain the decline of beta. Consistent with our model and Massa and Simonov (2006), we consider familiarity as information driven rather than a behavioral bias. Therefore, familiarity should be related to the length of time information is acquired by investors. Age of the firm should broadly capture this effect. To be more precise, we propose another proxy for familiarity. We use as a proxy for familiarity a cumulative information variable.[20] The idea is that the more historical information there is about a company, the more familiar an investor is with the company.

[19] Savor and Wilson (2014) document that asset prices behave very differently on days when important macro-economic news is scheduled for announcement. In particular, the stock market beta is positively related to average return only on announcement days consistent with the CAPM holding on announcement days but not on non-announcement days. We tested whether the decline in beta over age is stronger during non-announcement days. Although not reported in this paper, when we included the control variables we did not find any significant difference between the effect of age on beta between macro-announcement days and non-announcement days.

[20] Massa and Simonov (2006) use a unique data set of Swedish investors to construct the following measures of familiarity: (1) the holding period a stock has been in the investor's portfolio; (2) whether the investor's profession is in the same area of activity as the company; (3) the proximity between the residence of the investor and the place where the company is located. Unfortunately, equivalent data are not available for our US sample.

Table 7
Life-cycle stages and beta: Stock-level regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	−0.001	−0.001	−0.004	−0.003	−0.004	−0.003	−0.004	−0.002
	(−2.81)	(−2.58)	(−5.66)	(−4.90)	(−5.44)	(−4.47)	(−3.88)	(−2.66)
	***	***	***	***	***	***	***	***
Constant	1.755	1.479	1.424	1.169				
	(9.08)	(6.97)	(5.97)	(3.72)				
	***	***	***	***				
MLDA2	−0.274	−0.117						
	(−3.53)	(−1.94)						
	***	*						
MLDA3	−0.422	−0.229						
	(−4.44)	(−3.08)						
	***	***						
MLDA4	−0.032	−0.071						
	(−0.38)	(−0.82)						
DCS2			−0.293	−0.106				
			(−3.79)	(−1.77)				
			***	*				
DCS3			−0.427	−0.209				
			(−4.70)	(−3.00)				
			***	***				
DCS4			−0.086	−0.034				
			(−1.35)	(−0.58)				
RETA					−0.074	−0.047		
					(−3.90)	(−2.92)		
					***	***		
Adjusted age							−0.002	−0.001
							(−2.33)	(−2.07)
							**	**
Size	−0.012	−0.004	0.024	0.021	−0.012	−0.002	−0.016	−0.011
	(−0.93)	(−0.33)	(1.68)	(1.13)	(−0.90)	(−0.13)	(−1.23)	(−0.74)
			*					
B/M		−0.008		−0.017		−0.002		−0.044
		(−0.26)		(−0.42)		(−0.07)		(−1.22)
Leverage		0.002		0.000		0.002		−0.003
		(0.42)		(0.06)		(0.39)		(−0.43)
Payout ratio		−0.201		−0.170		−0.202		−0.229
		(−8.92)		(−9.00)		(−9.13)		(−8.53)
		***		***		***		***
Earnings variability		1.552		2.228		1.592		1.890
		(5.27)		(7.02)		(5.30)		(5.73)
		***		***		***		***
Earnings covariability		0.004		0.003		0.004		0.005
		(1.86)		(1.37)		(2.04)		(2.06)
		*				**		**
Liquidity beta		−0.068		−0.220		−0.082		−0.102
		(−0.60)		(−1.51)		(−0.75)		(−0.94)
Bid–ask spread		−2.318		−4.074		−2.045		−2.697
		(−1.41)		(−1.48)		(−1.34)		(−1.50)
N ∗ T	106,647	105,828	82,946	82,219	124,305	122,955	90,695	89,743
Adj R sq	0.019	0.034	0.019	0.039	0.019	0.033	0.017	0.037

Note: The table reports on the regressions of beta on life-cycle proxies and other variables of individual stocks. Following Faff et al. (2016), we calculate four alternative measures of the firm life-cycle: (i) multiclass linear discriminant analysis measure (MLDA), (ii) Dickinson's (2011) cashflow-based measure (DCS), (iii) earned to contributed capital ratio (RETA), and (iv) industry-size adjusted age (Adjusted age). MLDA1, MLDA2, MLDA3, MLDA4 are dummy variables (i.e., 0/1 variables) indicating whether the firm is in the intro stage (1), in the growth stage (2), in the mature stage (3), or in the shake-out or decline stage (4). DCS1, DCS2, DCS3, and DCS4 are defined similarly. See the notes to Table 1 for description of each variable. The estimation includes a constant term and dummy variables indicating whether each variable – other than beta, market cap, and B/M – is missing. The dataset has a panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

In particular, we accumulate the total information across past values, where total information is the sum of public and private information variables defined in Section 3.7. More precisely, we use this equation to compute our proxy of familiarity:

$$\text{Cumulative total information}_t = \sum_{K=0}^{N} (K+1) * \text{total information}_{t-K} \tag{24}$$

Table 8
Information and beta: Stock-level regression.

	(1)	(2)	(3)	(4)	(5)
Age	−0.007	−0.007	−0.005	−0.004	−0.004
	(−5.96)	(−6.49)	(−5.86)	(−5.48)	(−5.51)
	***	***	***	***	***
Size		0.019	0.028	−0.005	−0.008
		(1.51)	(1.70)	(−0.26)	(−0.43)
			*		
B/M			−0.019	−0.038	−0.037
			(−0.54)	(−1.17)	(−1.15)
Leverage			−0.003	−0.003	−0.003
			(−0.48)	(−0.58)	(−0.58)
Payout ratio			−0.165	−0.162	−0.159
			(−10.57)	(−10.34)	(−10.34)
			***	***	***
Earnings variability			2.087	1.924	1.945
			(6.57)	(5.94)	(6.00)
			***	***	***
Earnings covariability			0.002	0.002	0.002
			(0.92)	(0.76)	(0.77)
Liquidity beta			−0.092	−0.089	−0.087
			(−0.83)	(−0.79)	(−0.78)
Bid–ask spread			−3.407	−2.849	−2.954
			(−1.56)	(−1.32)	(−1.37)
Number of analysts				0.011	0.011
				(2.07)	(2.09)
				**	**
Dispersion				2.704	2.737
				(5.02)	(5.07)
				***	***
Public info				−3.775	
				(−4.28)	
				***	
Private info				−0.842	
				(−3.07)	
				***	
Public info share					−0.024
					(−0.44)
N ∗ T	90,745	90,745	89,533	89,533	89,533
Adj R sq	0.011	0.012	0.032	0.037	0.037

Note: The table reports on the regressions of beta on age and other variables of individual stocks between 1982 and 2016. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. See the notes to Table 1 for description of each variable. The estimation includes a constant term and dummy variables indicating whether each variable–other than beta, age, market cap, and B/M–is missing. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

where K represents the duration of total information in years and N is $t-1982$ (total information is not available for the years prior to 1982). Note that we are not simply summing past values of information; older information has a greater impact via the term K, since investors are exposed to older information for a longer period. Thus, we may interpret the new variable as the information-weighted age of the firm.

Next, we use our latest regression specification that includes the information variables and run a regression with this familiarity proxy. Table 10 presents the results. We consider two specifications one with age (see column (1)) and one without age (see column (2)). In both specifications, the cumulative information variable is significant in explaining beta. The sign is negative as expected. Interestingly, when we include both age and the cumulative information variable age becomes insignificant (see column (1)), which suggests that our new variable subsumes the explanatory power of age and that the significance of age in our previous analyses was coming from the correlation with familiarity. In columns (1) and (2), we exclude observations with missing values for the cumulative information variable. To avoid losing too many observations, we repeated the same analysis after filling missing values of the cumulative information variable with age. The results are shown in columns (3) and (4) of Table 10. The cumulative information variable continues to be significant.[21] In an untabulated test, we run the same regressions at the portfolio-level and continue to find that the cumulative information variable is significant.

[21] When both age and the cumulative information variable are included, age is significantly positive. This is due to the positive correlation introduced by filling the cumulative information variable with age.

Table 9
Information and beta: Portfolio-level regressions.

	(1)	(2)	(3)	(4)	(5)
Age	−0.006	−0.006	−0.004	−0.004	−0.004
	(−7.72)	(−5.70)	(−4.50)	(−4.35)	(−4.34)
	***	***	***	***	***
Size		−0.001	−0.029	−0.032	−0.037
		(−0.03)	(−1.19)	(−1.28)	(−1.52)
B/M			−0.095	−0.153	−0.140
			(−1.57)	(−2.64)	(−2.40)
				***	**
Leverage			0.003	0.003	0.003
			(0.28)	(0.26)	(0.26)
Payout ratio			−0.239	−0.239	−0.235
			(−4.75)	(−4.78)	(−4.68)
			***	***	***
Earnings variability			4.678	4.226	4.449
			(5.59)	(4.74)	(4.97)
			***	***	***
Earnings covariability			0.015	0.015	0.014
			(2.41)	(2.31)	(2.22)
			**	**	**
Liquidity beta			0.166	0.108	0.116
			(1.59)	(0.96)	(1.07)
Bid–ask spread			−3.115	−4.121	−3.991
			(−1.04)	(−1.32)	(−1.27)
Number of analysts				0.003	0.003
				(0.70)	(0.78)
Dispersion				2.276	2.382
				(3.19)	(3.32)
				***	***
Public info				−0.972	
				(−1.42)	
Private info				−1.158	
				(−2.40)	
				**	
Public info share					0.019
					(0.29)
N ∗ T	3431	3431	3431	3431	3431
Adj R sq	0.091	0.090	0.138	0.145	0.141

Note: The table reports on the regressions of beta on age and other variables of year–age portfolios between 1982 and 2016. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. We have sorted the stock-years of year t into 100 age portfolios corresponding to ages between 1 and 100; i.e., portfolio (t, a) includes stock-years of year t and age a. For each year–age portfolio, we have calculated beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, bid–ask spread, the number of analysts, dispersion, public info, private info, and public info share. Except for size, which is the equal-weighted average of individual stocks' size, all the other variables are the value-weighted average of the corresponding variables of individual stocks. See the notes to Table 1 for description of each variable. The estimation includes a constant term and dummy variables indicating whether each variable–other than beta, age, market cap, and B/M–is missing. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

5. Implications for the cost of equity Capital

The main finding of this paper is that beta declines with age and firm age serves as a proxy for firm risk that captures familiarity and uncertainty not captured by established accounting and fundamental factors. This finding has potentially important implications. One direct implication is that the decline in beta with age leads to a decline in the cost of equity capital. This implication stems from using the CAPM to estimate the cost of equity capital. The main issue is that, although the CAPM is used extensively in practice, it has been generally rejected in empirical academic studies. In this section we examine whether controlling for age is important for asset pricing tests of the CAPM. Next, we provide some practical guidance on how to compute the cost of equity for capital budgeting calculations.

Table 10
Familiarity and beta: Stock-level regression.

	(1)	(2)	(3)	(4)
Age	0.006 (1.31)		0.013 (2.46) **	
Cumulative information	−0.010 (−2.01) **	−0.004 (−4.87) ***	−0.017 (−3.09) ***	−0.004 (−5.50) ***
Size	−0.074 (−3.32) ***	−0.075 (−3.40) ***	−0.002 (−0.13)	−0.004 (−0.22)
B/M	−0.050 (−1.17)	−0.050 (−1.18)	−0.037 (−1.15)	−0.037 (−1.16)
Leverage	0.002 (0.35)	0.002 (0.31)	−0.003 (−0.50)	−0.003 (−0.55)
Payout ratio	−0.154 (−8.78) ***	−0.154 (−8.75) ***	−0.161 (−10.34) ***	−0.161 (−10.35) ***
Earnings variability	2.303 (5.94) ***	2.301 (5.94) ***	1.926 (5.95) ***	1.925 (5.95) ***
Earnings covariability	0.001 (0.39)	0.001 (0.40)	0.002 (0.75)	0.002 (0.76)
Liquidity beta	−0.076 (−0.68)	−0.075 (−0.68)	−0.090 (−0.81)	−0.089 (−0.80)
Bid–ask spread	−5.225 (−1.49)	−5.196 (−1.48)	−2.818 (−1.30)	−2.841 (−1.31)
Number of analysts	0.017 (3.18) ***	0.017 (3.14) ***	0.011 (2.21) **	0.011 (2.11) **
Dispersion	3.324 (5.44) ***	3.331 (5.46) ***	2.688 (4.96) ***	2.699 (5.01) ***
Public info	−2.330 (−3.29) ***	−2.515 (−3.29) ***	−3.240 (−4.03) ***	−3.636 (−4.16) ***
Private info	−0.397 (−1.54)	−0.440 (−1.67) *	−0.717 (−2.70) ***	−0.810 (−2.97) ***
$N * T$	47,272	47,272	89,533	89,533
Adj R sq	0.056	0.056	0.037	0.037

Note: The table reports on the regressions of beta on age and other variables of individual stocks between 1982 and 2016. The dataset has panel structure; we carry out OLS regressions, calculate double-clustered standard errors following Petersen (2009), Cameron et al. (2006), and Thompson (2006), and obtain t-statistics. See the notes to Table 1 for description of each variable. The cumulative information variable is our proxy for familiarity and is obtained by cumulating the sum of public and private information across past values. The estimation includes a constant term and dummy variables indicating whether each variable–other than beta, age, market cap, and B/M–is missing. Column (3) and (4) are the same regression as column (1) and (2) where we fill missing values of the cumulative information variable with age. The table reports the coefficient estimates and double-clustered standard errors-based t-statistics inside round brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

5.1. Asset pricing tests

Similar to Cohen et al. (2009) we take a long-horizon perspective to test the CAPM. Cohen et al. (2009) argue that a long-horizon perspective is preferable for many important decisions such as the decision of a corporate manager to make long-term business investments. This is precisely the perspective we are interested in when considering the implication of the decline in beta on the cost of equity capital, which is one of the main inputs for capital budgeting.

Following Cohen et al. (2009) we then test the ability of the CAPM to explain the cross-section of holding-period expected returns, which is measured by the price level, and examine whether conditioning on age is important for the success of the test. We expect this to be true for the following reasons. Given that beta declines with age, this can create a discount-rate effect that pushes prices higher. In this setting, realized returns tend to be a poor proxy of expected returns. However, when we control for age and take a long-horizon perspective, average realized returns may measure more accurately expected returns. Moreover, given that errors in measured beta is partly determined by firm age, creating age-sorted portfolios is more likely to reveal the true relationship between expected returns and beta.[22]

Cohen et al. (2009) calculate the 'price level' of portfolio k at time t as the cumulative N-period discounted portfolio return:

$$P_{k,t}^{N} = \sum_{j=1}^{N} \rho^{j} R_{k,t,t+j} \tag{25}$$

where $R_{k,t,t+j}$ refers to the year $t+j$ return of the portfolio k formed in year t, $\rho = 0.975$, and $N = 15$. Once portfolio k is formed at the end of year t, we keep it fixed and follow the returns of this portfolio for the next N-years, from which we determine the price level of this portfolio.[23]

Using the formula above, we compute the price level measure for 100 portfolios sorted using beta, B/M-size (10 B/M sorted portfolios are sorted again according to the size), or age. We use age information to form portfolios in two different ways. In the first approach, we sort stocks into 100 portfolios using age. In the second approach, we first sort the stocks into 20 portfolios using age and then sort within each age-sorted portfolio into 5 portfolios using beta for a total of 100 age–beta-sorted portfolios. For each portfolio-year $(k, t, t+j)$, we compute portfolio returns and then we compute the price level measure $P_{k,t}^{N}$ using the above formula. We then take the average across years to obtain the price level measure for portfolio k, $P_{k}^{N} = \sum_{t} P_{k,t}^{N}/T$, where T is the number of years.[24] Following Cohen et al. (2009), we annualized the price level measures by dividing by the annualization factor $\sum_{j=1}^{N} \rho^{j}$.

In Fig. 4, we plot the price level measure against average beta based on various sorts of the data.[25] In the top row of the figure, we show the plot of beta against the price level measure for a discounting period of 15 years (Cohen-15). When sorting on beta alone, the relationship between beta and expected return is unclear. When sorting on book-to-market and size, the relationship between beta and expected return is also absent. However, when we sort on age or double sort using age and beta, there is a positive relationship between beta and expected return. Mispricing is concentrated in the portfolios of age less than 10. Indeed, the positive relationship between beta and expected return is much stronger when we remove the portfolios with age up to 10. For these portfolios, expected return is likely to be measured inaccurately given that our sample contains only a small number of very young stocks and for very young firms the measurement error is more severe. The results in these figures support the CAPM prediction only when age is used as a sorting variable.

To confirm the existence of a positive and significant relationship between beta and expected return, we run Fama and MacBeth (1973) regressions. Specifically, each year we run cross-sectional regressions of the price level measures on portfolio betas. Then, we calculate the time-series means of these first-stage coefficient estimates. In the second stage, we adjust the standard errors using the Newey and West (1987) approach using the number of holding periods (15) minus one as the lag length. This approach corrects for cross-sectional and time dependence of the residuals, which is present due to the overlap of the observations. Table 11 shows the results. In the first specification, we sort using beta and the slope coefficient is positive but not statistically significant. This is consistent with the evidence of the failure of the CAPM. The slope is also insignificant when we use the B/M-size portfolios. Columns 3 and 4 examine the relationship between price level and beta when we use age as a sorting variable. For these cases, we run regressions with and without excluding the first 10 age portfolios. In both cases, the slope coefficient is positive and significant. Columns 5 and 6 examine the relationship between the price level and beta when we double sort using age and beta. The slope coefficient is once again positive and significant.

We made several variations of the analysis to check for robustness. First, we used individual stocks as test assets and run Fama–MacBeth regressions at the stock rather than portfolio level. We followed Fama and French (1992) and assign the portfolio's betas to each stock in the portfolio. Next, using individual stocks, we estimated regressions of the price level measures on beta and the control variables used in the previous regressions. We found that only when we control for age and use the betas computed from age-sorted portfolios or age–beta-sorted portfolios that there was a significant (at the 5% level) and positive relation between beta and expected return (we report these results in the Internet Appendix Table A14).

Second, we computed the price level measure using annual value-weighted portfolio returns rather than equally-weighted portfolio returns. The slope coefficients for beta and B/M-size portfolios are insignificant whereas it is positive and significant for the 100 age portfolios with a t-statistic of 1.99. Third, we excluded stocks with age up to 10 years and repeated the analysis using 100 beta-sorted portfolios. We find that the beta-return relationship becomes stronger after excluding the youngest firms. In particular, the slope coefficient is marginally significant (p-value of 0.08). Finally, we computed betas using the returns of the last 5 or 3 years instead of 15 years (i.e., from the next 10 or 12 to 15 years post ranking). Again, we find that the beta-return relationship becomes stronger (p-value of 0.08 with the last 5 years and p-value of 0.05 with the last 3 years). The last two analyses suggest that the change of beta over age (especially stronger for very young firms) is a source of the failure of the CAPM test and that using CAPM to estimate the cost of capital is appropriate for more mature firms.

[22] Fig. 1 shows that there are more young firms than old firms. Thus, creating age-sorted portfolios has the effect of not giving too much weight to young firms with large errors. If portfolios are created via beta sorting, young firms with large errors will create more distortions (we run simulations to confirm this statement).

[23] Note that year t is defined from July of the previous year to the end of June.

[24] To give a more concrete example of this formula, suppose we are computing the "price level" for the 10-year age–portfolio sorted on year t. Then starting in year $t+1$, we compute the returns for the next N years keeping the stocks in the portfolio fixed. We then discount the returns using the formula. In this sense, it represents the discounted price of a buy-and-hold 10-year old portfolio as we hold it for 15 years. Since for every t in our historical data sample, there will be a discounted price for the 10-year old portfolio, we can use this panel in the regressions and then average the price across years to get our measure of 'price level' that we use in the graphical representation.

[25] The betas are post-ranking betas. In every year t we compute the next 15 years portfolio returns and we estimate betas using Eq. (6). The time-series average of these betas is used in the chart.

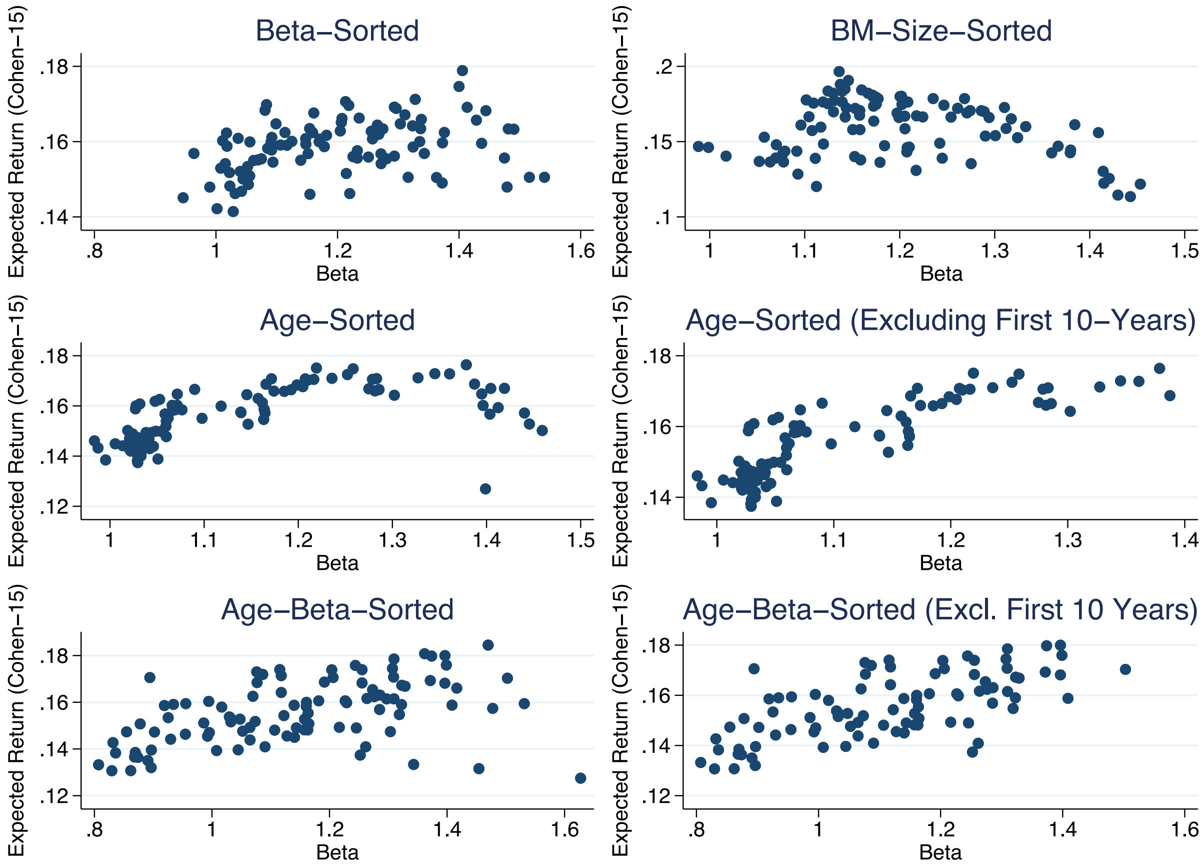

Fig. 4. Expected returns versus beta. *Note*: The plots show the holding-period expected return (the Cohen-15 price level measure) vs. beta of beta, B/M-size, and age sorted portfolios. The initial sample includes stock-years of non-financial common stocks in the CRSP-Compustat universe, of the period between 1966 and 2016, and of ages between 1 and 100. We have determined the age as the number of years (as of the end of June of year t) since incorporation or founding, whichever is earlier. We create different portfolios for each year t. Once portfolio (k,t) is created, we calculate returns of the portfolio for the next 15 years, from which we compute the price level measure $P^{15}_{k,t}$. See the text for exact formula. We also calculate post-ranking portfolio betas using the next 15 years portfolio returns. Ranking betas are instead estimated from weekly returns between July of year $t-1$ and June of year t. We then take the average of $P^{15}_{k,t}$ and post-ranking portfolio betas over years to obtain P^{15}_{k} and average beta. The price level measure is annualized by dividing by the annualization factor $\sum_{j=1}^{15}\rho^j$. The plots show P^{15}_{k} against average betas of different k's. For the first plot, 100 beta-sorted portfolios are created. For the second plot, 100 portfolios are created by sorting on B/M first and then on size. For the third plot, 100 portfolios are created based on age. For the fourth plot, 100 portfolios are created based on age and then we remove the portfolios from age 1 to 10. For the fifth plot, 100 portfolios are created by sorting on age first (20 portfolios) and then on beta (5 portfolios). From the sixth plot, we remove the first 2 age portfolios (with age less than and equal to 10 years) from the portfolios in the fifth plot.

One concern is the magnitude of the slope and intercept coefficients. Take for example, the third column, the slope estimate is 0.0369, which is 3.69% per year. If the CAPM holds, then this number should be the average market return over the risk-free rate. This number is lower than the historical risk premium (5.87% per year using the 1966–2016 sample period). The intercept is 0.1169, which is 11.69% per year. If the CAPM holds, then this number should be the risk-free rate. These two estimates – very high intercept and low slope – suggest that the relationship between expected return and beta is weaker than the CAPM predicts.[26] We take this finding as evidence that the CAPM is still an incomplete measure of risk. However, when we control for age, there is a positive risk-return tradeoff as implied by the theory. This result shows the importance of age as conditional variable to support the main empirical prediction of the CAPM and provides support for using the CAPM in long-term investment decisions as a useful although perhaps incomplete measure of risk. Similar to our paper, Cohen et al. (2009) also conclude by supporting the use of CAPM in capital budgeting. However, an important difference is that we advocate for the use of the traditional and most common way of computing beta based on stock returns, but accounting for age, rather than using beta computed from cash flows as proposed by Cohen et al. (2009).

[26] This is to be expected from the discussion in Section 2: the relationship between beta and return would appear weak if we do not adequately adjust for estimation risk an unfamiliarity premium.

Table 11
Expected returns vs. beta: Portfolio-level regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
Slope	0.0187	0.0217	0.0369	0.0430	0.0332	0.0420
	(1.07)	(1.27)	(2.11)	(3.17)	(2.27)	(3.06)
			**	***	**	***
Intercept	0.1383	0.1332	0.1169	0.1106	0.1191	0.1106
	(11.61)	(8.23)	(6.83)	(6.47)	(9.28)	(9.03)
	***	***	***	***	***	***

Note: This table reports results from Fama–MacBeth regressions of the price level measures on portfolio betas of beta (column 1), B/M-size (column 2), age sorted portfolios (columns 3 to 4), and age–beta sorted portfolios (columns 5 to 6). The initial sample includes stock-years of non-financial common stocks in the CRSP-Compustat universe, of the period between 1966 and 2016, and of ages between 1 and 100. We have determined the age as the number of years (as of the end of June of year t) since incorporation or founding, whichever is earlier. We create different portfolios for each year t. Once portfolio (k, t) is created, we calculate returns of the portfolio for the next 15 years, from which we compute the price level measure $P^{15}_{k,t}$. See the text for exact formula. We also calculate post-ranking portfolio betas using the next 15 years portfolio returns. Ranking betas are instead estimated from weekly returns between July of year $t-1$ and June of year t. The regressions use $P^{15}_{k,t}$ and post-ranking betas of different k's. For the first column, 100 beta-sorted portfolios are created. For the second column, 100 portfolios are created by sorting on B/M first and then on size. For the third column, 100 portfolios are created based on age and from these portfolios we remove the first 10 age portfolios for the fourth column. For the fifth column, 100 portfolios are created by sorting on age first (20 portfolios) and then on beta (5 portfolios). From these portfolios, we remove the first 2 age portfolios (with age less than and equal to 10 years) in the last column. t-statistics based on Newey–West standard errors are shown inside round brackets. *, **, and *** indicate significance at 10%, 5%, and 1% significance.

5.2. Practical implications for cost of equity calculation

One concern with the previous tests is that we used post-sorting betas. In practice only past information is available to compute betas for the cost of equity calculation. To provide practical guidance on how to use the CAPM for capital budgeting and at the same time adjust for the age effect, we performed additional tests where we only used past information to compute betas. Similar to Fama and French (1997) and Gode and Mohanram (2003), we evaluated competing approaches to estimate betas for the cost of equity calculation by examining the ability to predict future expected returns, proxied by the price level measure.[27] When using the risk loading in the cost of equity calculation, a minimum requirement is to have a positive relation between beta and future expected returns. Accordingly, we ran stock-level regressions of the price level on betas and controls where betas are ex-ante betas (using only past information) and obtained using alternative approaches. We considered betas obtained from past returns and industry betas, which are the two most common approaches to estimate betas in practice.[28] We also considered betas estimated from a portfolio of stocks with similar beta or book-to-market ratios. Our recommended approach is to use the beta of a portfolio of stocks with similar age. For example if a firm is 10 years old, we recommend using, in the CAPM calculation for cost of equity, the beta obtained using the returns of a portfolio of firms with 10 years of age.

Table 12 provides the results from our analysis and shows that we obtain a significant and positive relation only when we use the beta of age-sorted portfolios. We also obtain similar results when we use beta from sorting using both industry and age information. Hence, if one wants to use industry beta (for example if sufficient past returns' data are not available) then the suggestion is to use the beta from a portfolio of stocks in the same industry and with similar age. Overall, these findings suggest the importance of considering the age of the firm when estimating the beta for capital budgeting.

6. Conclusion

Measuring beta accurately is important for understanding securities markets. There have been numerous studies over the years attempting to understand the shortcomings and problems surrounding the measurement of beta. Our research adds to that literature by studying a neglected pattern of time variation associated with beta and the age of a company. We find that the beta of a company declines with age. This decline on average over a 20-year period is 0.14 and it is stronger for relatively young firms.

Our analysis suggests that the decline in beta over firm age is related to a declining premium on unfamiliarity. That is, for young companies, the measured beta is larger than normal due to the lack of familiarity. We find that firm characteristics, the amount and heterogeneity of information, and life-cycle stages explain the decline in beta only partially. The relationship between age and beta is strong even when we control for these variables. Some of this decline is captured by the size of the firm, but size does not entirely explain the decline in beta. That is, even though companies become larger over time and beta declines over time, when size and age are considered together to explain the decline of beta over time, size is not always significant and has a small effect

[27] The accounting literature starting with Botosan (1997) suggests to use analysts' forecasts to estimate the implied cost of capital (defined as the internal rate of return that equates the current stock price to the present value of future cash flows). However, Easton and Monahan (2005) examine the relation between future returns and implied cost of capital estimates and they find no significant positive relation.

[28] For example, the beta provided by yahoo finance is estimated using past 5 year of returns data using monthly observations. In our analysis we use 1 year of data and weekly observations. We also used 5 years of returns data and monthly observations and obtained similar results.

Table 12
Expected returns vs. ex-ante beta: Stock-level regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Stock beta	Industry beta	Beta-sorted portfolio beta	B/M-sorted portfolio beta	Age-sorted portfolio beta	Industry-age-sorted portfolio beta
Intercept	0.214	0.205	0.214	0.217	0.198	0.194
	(5.26)	(4.72)	(5.26)	(4.96)	(5.11)	(4.93)
	***	***	***	***	***	***
Beta	0.001	0.006	0.001	−0.001	0.009	0.009
	(0.91)	(1.44)	(0.94)	(−0.29)	(3.44)	(2.16)
					***	**
Size	−0.006	−0.006	−0.006	−0.006	−0.005	−0.005
	(−2.40)	(−2.28)	(−2.40)	(−2.39)	(−2.28)	(−2.22)
	**	**	**	**	**	**
B/M	0.008	0.009	0.008	0.008	0.009	0.009
	(4.49)	(4.87)	(4.48)	(4.88)	(5.39)	(5.93)
	***	***	***	***	***	***
Leverage	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.99)	(−1.86)	(−1.98)	(−1.90)	(−1.96)	(−1.64)
	**	*	**	*	**	*
Payout ratio	−0.007	−0.006	−0.007	−0.007	−0.006	−0.006
	(−3.46)	(−3.79)	(−3.46)	(−3.57)	(−3.06)	(−3.10)
	***	***	***	***	***	***
Earnings variability	0.030	0.028	0.031	0.037	0.033	0.023
	(0.52)	(0.47)	(0.52)	(0.58)	(0.54)	(0.43)
Earnings covariability	0.000	0.000	0.000	0.000	0.000	0.000
	(0.08)	(0.02)	(0.08)	(0.09)	(0.08)	(0.07)
Liquidity beta	0.002	0.000	0.002	0.008	0.006	0.003
	(0.09)	(0.01)	(0.11)	(0.43)	(0.29)	(0.14)
Bid–ask spread	−0.096	−0.078	−0.096	−0.065	−0.075	−0.095
	(−1.51)	(−1.24)	(−1.52)	(−1.19)	(−1.33)	(−1.52)

Note: This table reports results from stock-level Fama–MacBeth regressions of the price level measures on betas and control variables. The betas are ex-ante betas. They are computed using weekly stock returns of the past one year (column 1); computed at the portfolio level and then assigned to each stock in the portfolio using industry portfolios (column 2), 100 beta-sorted portfolios (column 3), 100 B/M-sorted portfolios (column 4), 100 age-sorted portfolios (column 5), and industry-age sorted portfolios (column 6). Portfolio-level betas are computed from weekly equal-weighted portfolio returns of the past one year. For the industry portfolios we use two digits SIC code; for the industry-age portfolios, we use one digit SIC code and 9 age groups. t-statistics based on Newey–West standard errors are shown inside round brackets. *, **, and *** indicate significance at 10%, 5%, and 1% significance.

on the coefficient for age. Age is a good proxy for the degree of familiarity that average investors have toward individual stocks. We discuss the implication of our findings for capital budgeting and suggest to use betas computed from a portfolio of firms with similar age for cost of equity calculation.

The evidence that beta declines with age has important implications for those who use beta to estimate the cost of capital for business projects. Adjusting beta for firm age improves the relevance of beta for the cost of capital calculation. We show that while there is an insignificant relationship between long-run expected returns and beta when age is ignored, this relationship becomes positive and significant when we control for age. Therefore, controlling for age is important for providing validity to the main CAPM prediction and justifying the continued use of the CAPM in capital budgeting.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2020.05.003.

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