The Life Cycle of Beta

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Abstract

The literature shows that beta is time-varying and difficult to predict using historically measured beta. We postulate that beta has an uncertainty component reflecting the life-cycle of the firm. Young firms are typically untested entities with considerable uncertainty. As this uncertainty resolves itself, the firm's beta declines. We document this decline and provide evidence that firm age is an important determinant. Fundamental factors and non-age proxies for information and uncertainty only partially explain this pattern. Considering a long-horizon perspective and using age as a conditioning variable, we provide support for the CAPM by finding a positive relationship between expected return and beta.

JEL Classification: G0
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1 Introduction

Despite the criticisms, the Capital Asset Pricing Model (CAPM) is used extensively in finance. For example, Graham and Harvey (2001) report that 73% of their firms use the CAPM to estimate the cost of equity capital. The only firm-specific input of the CAPM is the beta. Understanding the beta of a company is important for a vast amount of business applications, including 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 (e.g., Blume (1970, 1975) and Fama and French (1992)). Some of the stylized facts about empirical beta are that (1) measured betas tend to regress towards one; (2) larger portfolios have more stable betas than small portfolios and estimates of beta are more precise for portfolios than for single stocks; (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), Jagannathan and Wang (1996)); and (5) beta can't 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 (Patton and Verardo (2012)).

There are many reasons why beta could be time-varying and in particular could be higher for younger firms. One of the reasons may be that companies are dynamically changing and that inherently the risk of companies is constantly changing (Keim and Stambaugh (1986), Breen et al. (1989), Fama and French (1989), Chen (1991), Ferson and Harvey (1991), and Jagannathan and Wang (1996)). In fact, rather than discuss the beta of a company, we should really refer to the life cycle of beta for a company. For example, the information available to investors about a new, small company might be very sparse and consequently there is a larger amount of estimation risk associated with the company (i.e., greater uncertainty surrounding the exact parameters of its return distribution; see Clarkson and Thompson (1990)). However, as time passes, the company's beta might decline as the company grows, the nature of its business becomes better known to investors, and the uncertainty of both the parameters of the return-generating process and of the underlying cash flow covariance risk declines.

For a new company[1], uncertainty about the company will be higher as news events are only gradually released in the public markets. Some of the news will be bad and some good. Although we typically measure beta using historical data, news will affect the beta of a company the day of the news announcement and afterwards. Any type of news is more information about the company and thus might reduce the uncertainty about the company for investors (Ball and Kothari (1991)). This would seem to be especially true for small companies.[2] Patton and Verardo (2012) study the daily beta of stocks and how they react to earnings announcements and find that betas change on earnings announcement days and then revert to their averages within a few days after the announcement. They find that

[1] New can mean a newly traded public company. Thus, it's new in the sense that public information about the company is only recently available or new could mean a newly formed company as in relation to its incorporation date.

[2] Ball and Kothari (1991) find estimates of small firms' event-time systematic risk are consistent with both uncertainty resolution and the smaller firms' earnings being proportionally more informative. Kogan and Tang (2003) derive a two-factor model where expected returns also depend on the uncertainty of the portfolio held by the agent.

betas increase more for larger positive or negative announcements and for announcements with more information.[3] The documented evidence that beta changes over time may be related to multiple factors, including age. It is natural to assume that younger companies have more uncertainty as to the true valuation or risk of the company and thus, beta reflects both the uncertainty and some sort of intrinsic risk for the business. Using the age of a firm, investors and corporate managers might be able to untangle these effects in order to use a more accurate estimate of systematic risk.[4]

Another mechanism that could explain a decline of beta with age is obtained from a CAPM with heterogenous beliefs (e.g., Williams, 1997). There could be high systematic risk associated with high asymmetry of information for new corporations. Over time typically there is a decrease of information asymmetry and this results in a decrease of the systematic risk. Asymmetry of information is often proxied with the divergence of stock analyst forecasts. Some studies show that this divergence leads to abnormal returns (Anderson et al. (2005), Diether et al. (2002), and Doukas et al. (2006)).[5]

These results might be consistent with a life cycle of beta model. That is, new companies can be thought of as having a beta that is composed of an uncertainty piece in addition to the

[3]They believe that the beta increase is due to learning and cross-correlations with other stocks. Their paper focuses on larger, well established companies, which is less relevant to our primary concern of the life cycle of beta.

[4]For example, in securities fraud litigation, stock price reaction on news days is frequently measured to assess whether or not the market for the stock is efficient for use with fraud-on-the-market theory. Most of these studies fail to account for the fact that the companies beta changes on the day of the announcement due to the new information. This is another example of how information might change beta.

[5]These studies differ in their explanations of how analyst dispersion leads to abnormal returns. Diether et al. (2002) conclude that it is due to the resolution of uncertainty and thus lower future returns due to constraints. Anderson et al. (2005) find that both short-term and long-term measures of analyst dispersion lead to abnormal returns and that it matters more for small firms. Doukas et al. (2006) attempt to separate the uncertainty part of analyst dispersion from the difference of opinion using the technique of Barron et al. (1998) and find that difference of opinion of analysts is not priced by traditional factor pricing models, like Fama-French, and a positive alpha exist for stocks with high analyst difference of opinion.

co-variation with the market. Traditional measures of beta will be biased and inconsistent. As time passes, and more information is released about the new companies, this uncertainty factor declines and so does the measured beta of the firm. Thus, without removing the uncertainty component, the current beta is likely to be a poor predictor of future beta. By accounting for the life cycle of beta, we gain a better understanding of the time-variation of beta, which is important for estimating the cost of capital and to explain the failure of the CAPM. Capital budgeting ultimately involves measuring long-term risks correctly. Therefore, changes of beta over long-horizons are pivotal to this process.

In this paper, we study the beta over the life cycle of the firm. In particular, we sort stocks into different age cohorts and we regress the betas of the different portfolios on age. We find a significant and negative relation between age and beta. This decline in beta persists for almost 100 years. After documenting this pattern, we investigate whether we can explain it using fundamentals and different proxies for uncertainty and information. We find that age remains significant after including different explanatory variables. We interpret this result as age being a better proxy for the unknown risks of a company that decrease as a firm matures.

We conducted several robustness checks regarding age and beta. In particular, we confirmed that the pattern related to age was also present when we used the unlevered beta of firms. We also conducted the same analysis of beta and age on individual stock data in addition to the portfolio data and found the same pattern.

Clarkson and Thompson (1990) also found that stock market beta declines with the age of the firm during the first year that a company is listed on a stock exchange. The main contribution of our paper to the literature is to show 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 on average for 100 years. Our second contribution is to extend Clarkson and Thompson (1990) in examining the main drivers of the decline in beta. In particular, we consider other factors in addition to parameter uncertainty that may explain the decline.[6] At the same time, by considering not only fundamental variables, but also uncertainty and information variables we contribute to Beaver et al. (1970) in understanding the main drivers of the time variation in beta.

Finally, we show that it is important to control for age when considering a long-horizon perspective, which is relevant for capital budgeting decisions. In particular, we test the ability of the CAPM to explain the cross-section of holding-period expected returns, which is measured by the price level following 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. This finding constitutes another contribution of this paper by providing support for the main empirical prediction of the CAPM.

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.[7]

[6] Moreover, Clarkson and Thompson (1990) did not consider a proxy for parameter uncertainty as we do in this paper.

[7] Furthermore, researchers who use event studies in finance should pay attention to age. A popular

The paper is organized as follows. Section 2 describes the mathematics of estimating beta and its potential relation to the age of the firm; section 3 discusses the data and methodology for creating age cohorts; section 4 discusses the empirical findings of age and beta; section 5 discusses the asset pricing implications of age; and section 6 concludes.

2 The Life Cycle of Beta

2.1 Decomposition of Beta

Let's consider a conditional CAPM similar to Jagannathan and Wang (1996):

$$r_{i,t} = \alpha_i + \beta_{i,t} r_{m,t} + \epsilon_{i,t} \tag{1}$$

where $r_{m,t}$ is the excess return of the stock market, $r_{i,t}$ is the excess return of the stock i, and $\beta_{i,t}$ is the stock i conditional beta. Let $\beta_{i,t} = \beta_i + \gamma_i z_{i,t}$ where $\beta_i = E[\beta_{i,t}]$ and $z_{i,t}$ is the zero-mean time-varying component.[8] As shown by Jagannathan and Wang (1996) a conditional CAPM is equivalent to an unconditional multifactor model. Indeed,

$$r_{i,t} = \alpha_i + (\beta_i + \gamma_i z_{i,t}) r_{m,t} + \epsilon_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i z_{i,t} r_{m,t} + \epsilon_{i,t} \tag{2}$$

If this is true and we ignore the factor $z_{i,t}$, then the estimate from a simple one-factor CAPM estimation will be a biased and inconsistent estimator of β_i in the following way:

approach for measuring abnormal performance is to compare the performance of a stock against the performance of a benchmark (e.g., Daniel-Grinblatt-Titman-Wermers (1997) benchmark). Especially, when considering long-run performance it is important to understand how the beta changes over time and consider age could be an important control for constructing the benchmark. See Kothari and Warner (2007) for a review of long-horizon event studies.

[8] In the literature, the time-varying conditional betas $\beta_{i,t}$ have been commonly modeled as linear in instruments. These instruments can be firm-specific (e.g., Kumar et al. (2008)) and/or macro variables (e.g., Ferson and Harvey (1991)).

$$\hat{\beta}_i = \beta_i + \frac{\widehat{\text{Cov}}(r_{m,t}, \gamma_i z_{i,t} r_{m,t} + \epsilon_t)}{\widehat{\text{Var}}(r_{m,t})} = \beta_i + \gamma_i \frac{\widehat{\text{Cov}}(r_{m,t}, z_{i,t} r_{m,t})}{\widehat{\text{Var}}(r_{m,t})} + \frac{\widehat{\text{Cov}}(r_{m,t}, \epsilon_t)}{\widehat{\text{Var}}(r_{m,t})} \rightarrow \beta_i + \gamma_i \frac{\text{Cov}(r_{m,t}, z_{i,t} r_{m,t})}{\text{Var}(r_{m,t})} \tag{3}$$

Given that $z_{i,t}$ has zero mean, we can also show that[9]

$$\text{Cov}(r_{m,t}, z_{i,t} r_{m,t}) = \text{Cov}(r_{m,t}^2, z_{i,t}) - E[r_m]\text{Cov}(r_{m,t}, z_{i,t}). \tag{4}$$

Equation (3) and (4) show that firm-specific information, $z_{i,t}$, can affect the estimated beta, which is used as a measure of systematic risk and as an input in CAPM to compute the expected return if the information is correlated with the market return or the square of the market return. Our hypothesis is that the difference between the measured β_i and the true β_i of the company (i.e., the last term in Equation (3)) will decline over time. Thus, when the traditional measure of beta is used with new companies, the bias in beta will be larger than when estimated for older companies.[10] The bias in beta depends on the two covariances in Equation (4). These covariances could change over the life-time of a corporation for a variety of reasons. For example, if $z_{i,t}$ represented the uncertainty with a company's business or risk, this might naturally decline with age because often young corporations are involved in new productive activities that are better understood over time. Therefore, this uncertainty could be more correlated with the uncertainty about the market for younger firms than older firms.

[9] Indeed, ignoring the i and t subscripts we have:

$$\text{Cov}(r_m, z r_m) = E[r_m^2 z] - E[r_m]E[z r_m] = \text{Cov}(r_m^2, z) - E[r_m]\text{Cov}(r_m, z)$$

[10] This also implies that the R^2 of the estimation will decline with age as follows:

$$R^2 = 1 - \frac{\widehat{\text{Var}}(\gamma_i z_{i,t} r_{m,t} + \epsilon_t)}{\widehat{\text{Var}}(r_t)} = 1 - \gamma_i^2 \frac{\widehat{\text{Var}}(z_t r_{m,t})}{\widehat{\text{Var}}(r_t)} \frac{\widehat{\text{Var}}(\epsilon_t)}{\widehat{\text{Var}}(r_t)} \tag{5}$$

Equation (2) can be motivated via parameter uncertainty as well. There is a large literature on parameter uncertainty (also called estimation risk). Barry (1978), Barry and Brown (1985), Coles and Lowenstein (1988), and Clarkson (1986) have considered beta estimation by investors who face uncertainty over the exact parameters of the joint return distribution. Kumar et al. (2008) construct a model where investors are uncertain about the parameters of the return distribution and about the precision or quality of firm-specific information. Such a model suggests that information quality determines the estimation error (of return moment estimates), which in turn affects the equilibrium expected returns since Bayesian investors care about estimation error in their portfolio choice. Such reasoning justifies the inclusion of z in equation (2) and (3). Lambert et al. (2007) show that improvements in information quality by firms affect the beta and the cost of capital. Through somewhat different reasoning, Armstrong et al. (2012) show that firm-specific information can affect expected returns if it affects investor uncertainty about beta.

2.2 Diversification

For information and uncertainty (z in Equation (3)) and estimation error (which can be thought of as a transformation of z) to be the causal factor would require that these quantities cannot be diversified away in portfolios. Regarding the latter, Banz (1981) and Reinganum and Smith (1983) suggest that estimation risk should be largely diversifiable in a market with many securities. On the other hand, in a CAPM framework, the literature has shown that differential estimation risk generally has a systematic component and should be priced to some degree. For example, Handa and Linn (1993) suggest that systematic components to estimation risk are potentially important, even in well-diversified economies.

Another issue raised first by Barry and Brown (1985) is whether the increased uncertainty perceived by investors is observable to researchers in realized rate of return data. If estimation risk is not observed by researchers who study historical data, then there would have been an additional component of risk added by investors over and above observable risk measures. This might explain why small, less established, low information firms seem to have average abnormal returns relative to large, well established, high information firms. However, Clarkson and Thompson (1990) argue that the increased risk perceived by investors should be observable to researchers in realized rate of return distributions. Indeed, uncertainty should cause increased cross-sectional variability in stock prices and the resolution of the uncertainty over time creates price adjustments.

Information asymmetry may reduce the potential for diversification. Easley and O'Hara (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. 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.

Lambert et al. (2007) examine whether and how public accounting reports and disclosures affect a firm's cost of equity capital in the presence of diversification. They demonstrate that the quality of accounting information can influence the cost of capital, both directly and indirectly. The direct effect occurs because higher quality disclosures affect the firm's assessed covariances with other firms' cash flows, which is non-diversifiable. Therefore, earnings quality can affect the cost of capital via a firm's beta. The indirect effect occurs because higher quality disclosures affect a firm's real decisions, which likely changes the firm's ratio of the expected future cash flows to the covariance of these cash flows with the sum of all the cash flows in the market.

Thus, there is substantial evidence that information and uncertainty effects may not be easily diversifiable, and hence have a real effect on securities. Thus, betas might decline with age and be consistent with non-diversifiable information and uncertainty effects. However, the decline could be caused by a change in some of the fundamentals identified by Beaver et al. (1970) such as earnings variability and leverage. It is therefore important to control for fundamentals when investigating the behavior of betas over time. It is also important to include both the effects of private and public information. Indeed, as pointed out by Botosan et al. (2004), whereas both greater private and public information reduce the estimation risk, the effect on information asymmetry is in opposite direction. Indeed, greater private (public) information increases (mitigates) information asymmetry, which may play a role in the life cycle of beta.

3 Data and Methodology

3.1 Data

The sample used in this study includes all common stocks that are 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 sectors[11] 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.[12] 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.

3.2 Beta Measure

Our beta is estimated from weekly returns.[13] For year t, beta is based on weekly 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 adopted the Dimson's (1979) technique; we included the lagged market returns as regressors so that our regression equation was

$$r_t = \alpha + \beta_1(r_{M,t}) + \beta_2(r_{M,t-1}) + \beta_3(r_{M,t-2} + r_{M,t-3} + r_{M,t-4})/3 + \varepsilon_t \tag{6}$$

[11]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.

[12]This is to make sure that we can estimate the beta of every stock as of the end of June of each year.

[13] 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. 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.

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

To measure the uncertainty in the beta estimation, we use the standard deviation of the beta estimates. As our beta is the sum of three coefficient estimates, we make sure to consider the covariances among the estimates.[14]

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.[15] 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. Figure 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

[14]Thus, our measure is calculated as $\mathrm{SD}(\hat{\beta}) = \sqrt{(V(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3))} = \sqrt{(V(\hat{\beta}_1) + V(\hat{\beta}_2) + V(\hat{\beta}_3) + 2\mathrm{Cov}(\hat{\beta}_1, \hat{\beta}_2) + 2\mathrm{Cov}(\hat{\beta}_2, \hat{\beta}_3) + 2\mathrm{Cov}(\hat{\beta}_3, \hat{\beta}_1))}$.

[15]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. 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.

that were five years old and zero companies that were 100 years old.

[INSERT FIGURE 1 ABOUT HERE]

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 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 stock, 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 of 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.

In addition to the standard error of beta as an uncertainty measure, we also compute two uncertainty proxies based on earnings. The first is earnings variability, which is computed as the standard deviation of the earnings-to-price ratios of the 12 quarters ending on or before 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 Information Measures

In order to measure uncertainty or the information level of certain companies, we use several proxies. 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 file, 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 precision of public information, we follow Botosan et al. (2004)(BPX). 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 BPX (2004). It is $\frac{D}{(SE-D/N+D)^2}$. We also follow BPX by adjusting 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 the sum of the precision of public information and the precision of private information. We can also calculate the share of public information on a given security as the precision of public information divided by the precision of total information.

3.6 Other 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 an important determinant of cost of capital (e.g., Amihud and Mendelson (2000)) and liquidity is considered a priced state variable (e.g., Pastor and Stambaugh, 2003). 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.

Table 1 reports the summary statistics for our key variables.[16] 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. 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 standard error of the beta estimates is 1.18, 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.

[INSERT TABLE 1 ABOUT HERE]

4 Empirical Analysis

4.1 Beta and Age

We classify all stocks by age. Our age indicates the year that the company was incorporated and/or founded.[17] Between 1966 and 2016, we classified stocks by their age in every year creating age cohorts. Thus, a stock that was founded or incorporated between July 1, 1970

[16] 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 is 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 do this, since we are trimming our observations in the belief that extreme values are probably errors (not because extreme values are just extreme). We believe it made more sense to consider the entire sample when determining the appropriate trim values. We applied left and right trimming to liquidity beta, B/M, earnings yield, earnings covariability. We applied right trimming only to beta standard error, 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.

[17] In unreported analyses we also looked at another definition of age, using the IPO date of a firm to measure its birth. The qualitative results were similar.

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 created 101 age-cohort portfolios (Age 0 to Age 100) for every year. We then dropped the year 0 cohort from our analysis since, an entry stock might enter as year 0 or as year 1. We use the age of stocks in conjunction with other variables to understand the effects of age on beta.

In order to examine our hypothesis, we constructed a beta for each age cohort. Thus, we first estimated the beta of each individual stock in our database for each year as described in Section 3.2. We then calculated 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.

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

$$\beta_{t,a} = \gamma_0 + \gamma_1 a_t + \mathbf{\Gamma X}_t + \epsilon_{t,a} \tag{7}$$

where γ_1 represents the relationship between the age of the portfolio of companies and the portfolio's average beta, and $\mathbf{\Gamma}$ represents the coefficients on a set of variables, $\mathbf{X}$. We used two regression methodologies to understand the effect of age on beta. The first was a panel regression, whereby we take all observations from every year in our sample with betas and corresponding independent variables and run one regression. We also computed 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 was a Fama-MacBeth regression. Each year we ran a cross-sectional regression, estimated the parameters, and then averaged the parameters across all years.

4.2 Age, Fundamentals, Uncertainty, and Beta

In order to untangle the different sources influencing beta, we considered several specifications of our regression equations. Table 2 shows the results from several specifications where portfolio betas are regressed in a pooled regression against age and other factors. Column (1) shows a simple regression of 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, uncertainty proxies, and illiquidity proxies.

[INSERT TABLE 2 ABOUT HERE]

In all estimations, average portfolio beta declines with age. The coefficient, γ_1 is between -0.003 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 is depicted in Figure 2 for both the equal-weighted and value-weighted portfolios. In the first few years, due to the small number of stocks in the portfolios the beta pattern is not clear, but then beta steadily declines from year 5 to year 100 from 1.74 to 1.06 for the equal-weighted portfolio.[18] Size, payout ratio, earnings variability, and earnings covariability are the only other variables significant in determining the beta of a company. Earnings covariability represents a fundamental determinant of beta. Size and variability in earnings reflect the uncertainty in a company's future prospects and/or earnings. Payout ratio, as suggested by Beaver et al. (1970), can also be viewed as a proxy for management's perception of the uncertainty associated with the firm's earnings.

[18]This represents a coefficient closer to -0.007.

A significant correlation between beta and earnings variability, payout ratio, and earnings covariability was also documented by Beaver et al. (1970). However, neither fundamental factors nor most uncertainty measures are able 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.

[INSERT FIGURE 2 ABOUT HERE]

In Table 3, we also show the Fama-MacBeth results for beta on age and beta on age and size. Different estimation techniques do not alter this basic result. Untabulated results also show that the effect of age on beta is robust when we include the other control variables in the Fama-MacBeth specification.

[INSERT TABLE 3 ABOUT HERE]

We also find that our uncertainty proxies decline with the age of the company and information measures increase. We show this graphically in Figure 3. 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, these variables tend to be insignificant in explaining beta, when age is included in the regressions.[19]

[INSERT FIGURE 3 ABOUT HERE]

[19] We also checked whether the beta decline might be related to survivorship bias, in that high beta companies might die over time. We found that the age-beta relationship remains intact even when looking at only survivor companies.

4.3 Information and Beta

In the previous section, we showed that an important driver of declining beta is age, which is not subsumed by fundamental variables or certain proxies for uncertainty of beta. 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 become available on a company, then beta might be 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 are our proxies for the amount of available information on a company. We also use the precision of public and private information from BTX to understand its potential influence on the beta of a company. Table 4 shows the results from several pooled regressions. 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, fundamentals, and uncertainty factors. Column (4) and (5) show the results of regressions of beta on age, fundamentals, uncertainty, and the new information factors.

[**INSERT TABLE 4 ABOUT HERE**]

The earlier results remain qualitatively the same in the period from 1982 to 2011; age still influences beta. However, 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. Earnings variability, payout ratio, and earnings covariability continue to have a significant role in explaining beta. The number of analysts does not explain beta, but the dispersion of analyst forecasts does affect the beta. The precision of public information does not affect beta, but private information statistically affects beta. The negative coefficient indicates that as the precision of private information increases, beta declines.

Overall, the story is the same. The age of a company affects its beta, even when controlling for uncertainty proxies, fundamental proxies, and information proxies. There is something unique about age.[20]

4.4 Leverage and Beta

Basic fundamental factors are insufficient to explain the decline in beta with age. In our previous analysis, 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 will be different 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 un-levering it in the following way.

$$\beta_u = \beta_t \frac{(1 + L_t)}{(1 + L_{t-1})} \tag{8}$$

[20] Another way to differentiate between firm-specific news that might affect uncertainty relates to a paper by Savor and Wilson (2014). They 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, reflecting the resolution of firm-specific uncertainty. 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.

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 $t-1$. [21] Because of data errors or otherwise, 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 change. The coefficient on age is remarkably robust to these changes and age is statistically significant in explaining beta.

[INSERT TABLE 5 ABOUT HERE]

4.5 Stock Level Regressions

All of our results documenting the relationship between age and beta come from estimation of portfolios of stocks of different age cohorts on the beta of such groups. In order to ensure that these results are not being driven by some artifact of portfolio construction, we also performed a similar analysis with individual stock regressions. For the stock level regressions, we present fixed-effect estimates, i.e. the within-firm variation in beta is related to the within-form variation in age and other explanatory variables. The results are shown in Table 6 for the 1966-2016 sample period and Table 7 for the 1982-2016 sample period.

[21] 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.

The results are consistent with our earlier work; age is a significant determinant of the beta of a company even when running individual regressions at the stock level. In the full specification, more of the uncertainty and information variables are significant. Despite the additional variables appearing statistically significant in a way we would expect, age is still significant.

[INSERT TABLE 6 ABOUT HERE]

[INSERT TABLE 7 ABOUT HERE]

5 Asset Pricing Implications

The main finding of this paper is that beta declines with age and firm age serves as a proxy for firm risk that captures uncertainty not captured by established accounting and fundamental factors. This finding has potential 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. 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 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 reason. 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, average realized returns may measure more accurately expected returns.

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

$$P_{k,t}^{N} = \sum_{j=1}^{N} \rho^{j} R_{k,t,t+j} \tag{9}$$

where $R_{k,t,t+j}$ refers to the year $t+j$ return of the portfolio k formed in year t and $\rho = 0.975$ 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.[22]

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. 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

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

to obtain the price level measure for portfolio k, $P_k^N = \sum_t P_{k,t}^N / N$.[23] Following Cohen et al. (2009), we annualized the price level measures by dividing by the annualization factor $\sum_{j=1}^{N} \rho^j$.

In Figure 4, we plot the price level measure against average beta based on various sorts of the data.[24] In the top row of the figure, we show the plot 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 absent. When sorting on book-to-market and size, the relationship between beta and expected return is also absent. However, when we sort on age, there is a positive relationship between beta and expected return. Misspricing 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 first 10 age portfolios. For these portfolios expected returns is likely to be measured inaccurately given that our sample contains only a small number of very young stocks and furthermore for very young firms the changes in beta is more severe. These figures give support to the idea that only when age is used as a sorting variable do we obtain the CAPM prediction.

[INSERT FIGURE 4 ABOUT HERE]

[INSERT TABLE 8 ABOUT HERE]

[23]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 discount then 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.

[24] The betas are post-ranking betas. In every year t we compute the next 15 years portfolio returns and we estimate betas using equation (6). The time-series average of these betas is used in the chart. We tried to use the betas computed during the sorting year and we obtain similar results.

To confirm the existence of a positive and significant relationship between beta and expected return, we run Fama-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 as lag the number of holding periods (15) minus one. This approach corrects for cross-sectional and time dependence of the residuals, which is present due to the overlap of the observations. Table 8 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. Column 3 examines the relationship between price level and beta when we use age as a sorting variable. For this case we used a horizon of 15 years (Cohen-15) with and without excluding the first 10 age portfolios. In both cases, the slope coefficient is positive and significant.[25]

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

[25] As robustness, we also computed the Cohen-15 measures 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.

CAPM predicts. 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).

6 Conclusion

Measuring beta accurately is important for understanding securities markets. There has 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.

The decline in beta over the life cycle could be related to a declining uncertainty about the company. That is, the measured beta is on average larger than normal due to greater uncertainty associated with the company. In this sense, age is a proxy for the uncertainty about a company. However, we also find that the non-age proxies for uncertainty explain the decline in beta poorly. In fact, we find that the relationship between age and beta is strong even when we control for the non-age proxies of uncertainty. Although some of this could be captured by the size of the firm, size does not entirely explain it. That is, even though companies become larger over time and beta declines over time, when size and age are considered together in explaining the decline of beta over time, size is not always significant and has little effect on the coefficient for age. Thus, age is an important determinant of such a decline.

Our results that beta declines with age have important implications for those that use beta to estimate the cost-of-capital for business projects. Any forecast of beta over time may be adjusted for the age change in a company. This adjustment could be easily incorporated given that the time-variation in beta depends on a variable – age – which is known at the time of the forecast. Furthermore, we show that while there is an insignificant relationship between long-run expected return and beta when age is ignored, this relationship becomes positive and significant when we control for age. Therefore, controlling for age is important to provide validity of the main CAPM prediction and to justify the continued use of the CAPM in capital budgeting.

6.1 Figures

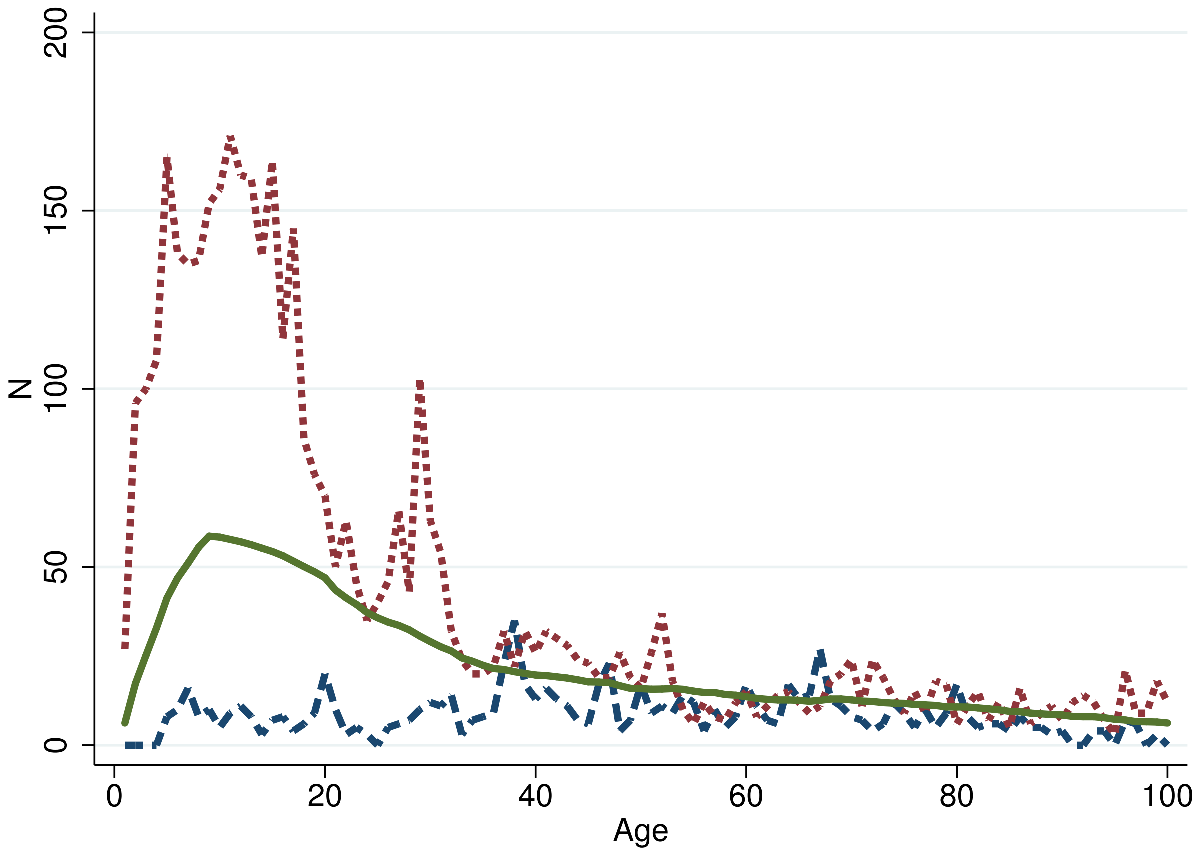

Figure 1: Age Distribution of the Sample Data

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.

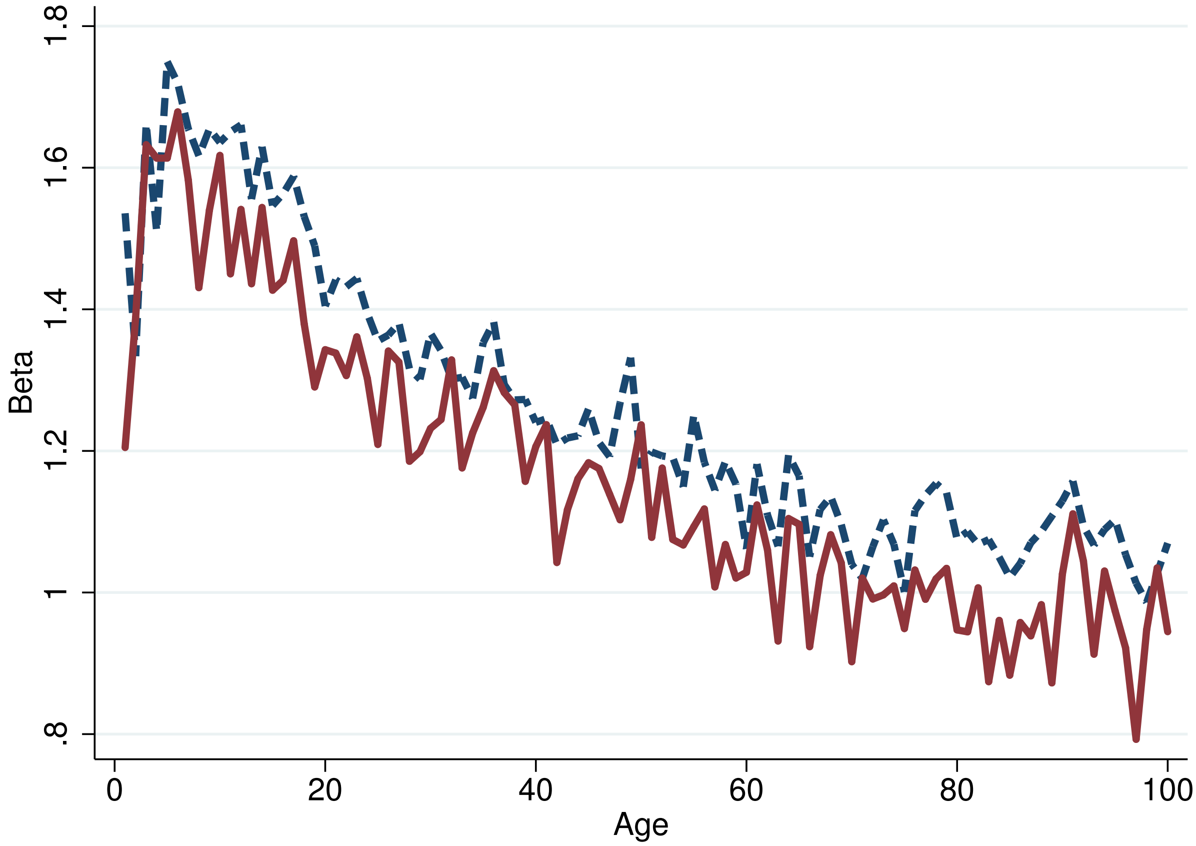

Figure 2: The Decline of Beta with Age

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 average of these values across years holding age fixed.

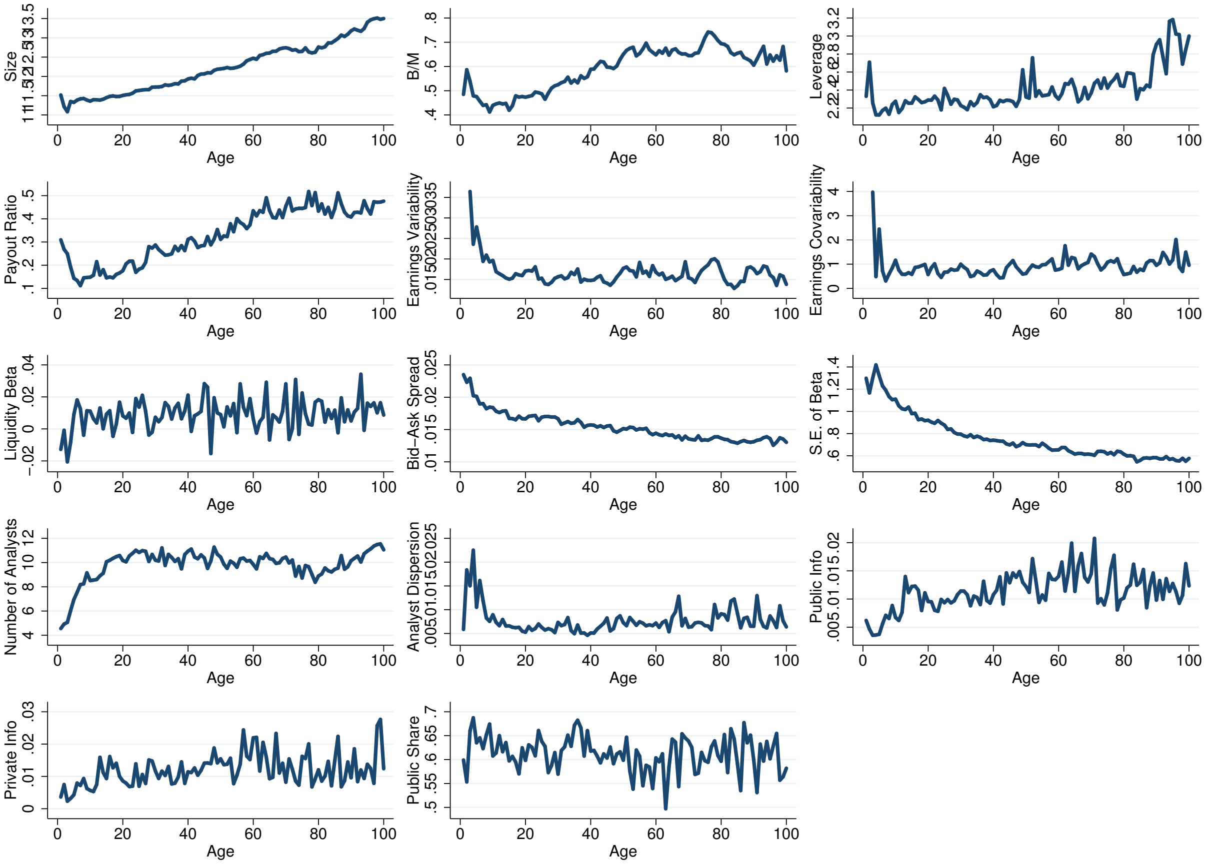

Figure 3: Other Variables with Age

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.

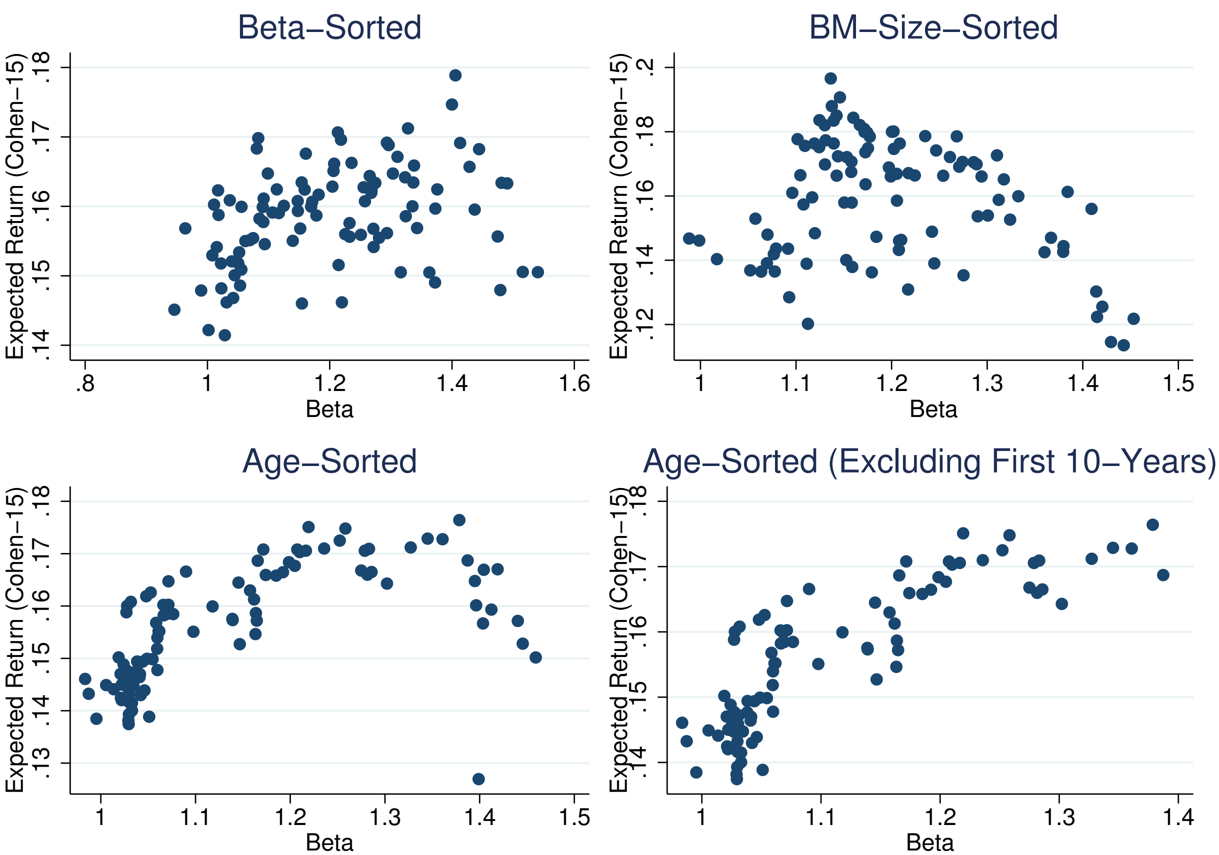

Figure 4: Expected Returns versus Beta

Note: The plots show the holding-period expected return (the 'price level') 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 $P_{k,t}^{15}$. 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 average of $P_{k,t}^{15}$ and post-ranking portfolio betas over years to obtain P_k^{15} and average beta. The price level measure is annualized by dividing by the annualization factor $\sum_{j=1}^{N} \rho^j$. The plots show P_k^{15} 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.

6.2 Tables

Table 1: Summary Statistics

Variable	Obs	Mean	SD	Min	Median	Max
Beta	114635	1.34	1.53	-20.14	1.22	21.44
Age	114635	33.89	25.48	1	26	100
Market cap	114635	1390.81	8863.48	0.59	140.20	715599.81
B/M	113679	0.76	0.65	0.02	0.58	5.27
Leverage	114117	2.37	2.13	1	1.82	30.06
Payout ratio	85351	0.23	0.43	0	0.05	5.75
Earnings variability	87493	0.03	0.05	0.0002	0.02	0.53
Earnings covariability	87107	1.08	6.17	-33.58	0.39	53.51
Liquidity beta	113529	0.01	0.17	-1.59	0.001	1.72
Bid-ask spread	114407	0.03	0.03	0.0001	0.02	0.21
SE of beta	114209	1.18	0.73	0.04	0.99	5.18
Number of analysts	70873	4.42	4.86	0	2.67	26.83
Dispersion	56641	0.01	0.03	0	0.004	0.61
Public info	17792	0.01	0.02	0	0.002	0.17
Private info	17781	0.01	0.02	0	0.001	0.29
Public info share	17839	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. **SE of beta** is the standard error associated with the beta. **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).

Table 2: Portfolio-Level Regression

	(1)	(2)	(3)
Age	-0.007	-0.006	-0.003
	[-26.09]	[-19.09]	[-8.73]
	{-10.68}	{-7.03}	{-4.91}
	***	***	***
Size		-0.041	-0.043
		[-5.89]	[-3.91]
		{-2.14}	{-3.06}
		**	***
B/M			-0.119
			[-4.41]
			{-1.91}
			*
Leverage			0.007
			[1.21]
			{0.69}
Payout ratio			-0.267
			[-9.01]
			{-5.88}
			***
Earnings variability			3.067
			[5.67]
			{3.71}
			***
Earnings covariability			0.019
			[5.42]
			{3.33}
			***
Liquidity beta			0.074
			[0.92]
			{0.81}
Bid-ask spread			2.695
			[2.66]
			{1.11}
SE of beta			0.121
			[5.16]
			{1.10}
N*T	4,964	4,964	4,964
Adj R sq	0.120	0.126	0.173

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 regression, calculate double-clustered standard errors following Petersen(2009), Cameron, Gelbach, and Miller (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, and standard error of beta. 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, ordinary t-statistics inside square brackets, and double-clustered standard errors-based t-statistics inside curly brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. The significance is for double-clustered standard errors-based t-statistics.

Table 3: Portfolio-Level Regression, Fama-MacBeth Estimation

	(1)	(2)
Age	-0.007	-0.005
	[-11.86]	[-8.19]
	***	***
Size		-0.068
		[-4.11]
		***

Note: The table reports on the regressions of beta on age and 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 square brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

Table 4: Portfolio-Level Regression, Post-1982 Period

	(1)	(2)	(3)	(4)	(5)
Age	-0.006	-0.006	-0.004	-0.003	-0.003
	[-18.51]	[-15.08]	[-7.56]	[-6.81]	[-6.83]
	{-7.72}	{-5.70}	{-4.00}	{-3.93}	{-3.92}
	***	***	***	***	***
Size		-0.001	-0.025	-0.031	-0.035
		[-0.09]	[-1.68]	[-1.97]	[-2.24]
		{-0.03}	{-1.02}	{-1.21}	{-1.42}
B/M			-0.079	-0.134	-0.119
			[-2.07]	[-3.28]	[-2.92]
			{-1.30}	{-2.34}	{-2.03}
				**	**
Leverage			0.003	0.003	0.003
			[0.45]	[0.40]	[0.40]
			{0.26}	{0.23}	{0.23}
Payout ratio			-0.232	-0.232	-0.228
			[-6.93]	[-6.94]	[-6.80]
			{-4.81}	{-4.89}	{-4.76}
			***	***	***
Earnings variability			4.440	4.047	4.233
			[6.96]	[6.27]	[6.56]
			{5.16}	{4.38}	{4.58}
			***	***	***
Earnings covariability			0.015	0.015	0.015
			[3.64]	[3.61]	[3.52]
			{2.42}	{2.32}	{2.23}
			**	**	**
Liquidity beta			0.172	0.113	0.121
			[2.00]	[1.29]	[1.38]
			{1.55}	{0.97}	{1.06}
Bid-ask spread			-2.951	-3.937	-3.789
			[-2.24]	[-2.95]	[-2.83]
			{-0.96}	{-1.23}	{-1.17}
SE of beta			0.070	0.071	0.079
			[2.60]	[2.59]	[2.86]
			{0.63}	{0.67}	{0.73}
Number of analysts				0.004	0.005
				[1.96]	[2.19]
				{1.28}	{1.42}
Dispersion				2.231	2.327
				[3.12]	[3.25]
				{3.02}	{3.13}
				***	***
Public info				-0.850	
				[-1.18]	
				{-1.32}	
Private info				-1.152	
				[-2.37]	
				{-2.34}	
				**	
Public info share					0.025
					[0.51]
					{0.39}
N*T	3,431	3,431	3,431	3,431	3,431
Adj R sq	0.091	0.090	0.139	0.146	0.143

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 regression, calculate double-clustered standard errors following Petersen(2009), Cameron, Gelbach, and Miller (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, standard error of beta, 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, ordinary t-statistics inside square brackets, and double-clustered standard errors-based t-statistics inside curly brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. The significance is for double-clustered standard errors-based t-statistics.

Table 5: Portfolio-Level Regression: Unlevered Beta

	(1)	(2)	(3)
Age	-0.007	-0.006	-0.004
	[-25.83]	[-19.34]	[-9.04]
	-10.26	-7.00	-5.09
	***	***	***
Size		-0.036	-0.036
		[-4.95]	[-3.22]
		-1.85	-2.65
		*	***
B/M			-0.107
			[-3.83]
			-1.65
			*
Leverage			0.003
			[0.52]
			0.32
Payout ratio			-0.270
			[-8.81]
			-6.16
			***
Earnings variability			3.169
			[5.66]
			3.90
			***
Earnings covariability			0.020
			[5.37]
			3.54
			***
Liquidity beta			0.059
			[0.71]
			0.66
Bid-ask spread			2.630
			[2.51]
			1.08
SE of beta			0.127
			[5.23]
			1.11
N*T	4,964	4,964	4,964
Adj R sq	0.118	0.122	0.167

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 regression, calculate double-clustered standard errors following Petersen(2009), Cameron, Gelbach, and Miller (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, bid-ask spread, and standard error of beta. 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, ordinary t-statistics inside square brackets, and double-clustered standard errors-based t-statistics inside curly brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. The significance is for double-clustered standard errors-based t-statistics.

Table 6: Stock-Level Regression

	(1)	(2)	(3)
Age	-0.007	-0.006	-0.002
	[-37.45]	[-35.34]	[-12.51]
	{-6.16}	{-5.70}	{-3.83}
	***	***	***
Size		-0.012	0.014
		[-5.10]	[4.68]
		{-0.88}	{0.90}
B/M			0.047
			[6.13]
			{1.43}
Leverage			0.002
			[0.81]
			{0.32}
Payout ratio			-0.146
			[-12.12]
			{-7.79}
			***
Earnings variability			1.228
			[11.57]
			{4.61}
			***
Earnings covariability			0.004
			[4.86]
			{1.87}
			*
Liquidity beta			-0.117
			[-4.63]
			{-0.98}
Bid-ask spread			-3.003
			[-13.98]
			{-1.79}
			*
SE of beta			0.276
			[38.83]
			{3.03}
			***
N*T	114,635	114,635	112,920
Adj R sq	0.012	0.012	0.041

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 regression, calculate double-clustered standard errors following Petersen(2009), Cameron, Gelbach, and Miller (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, ordinary t-statistics inside square brackets, and double-clustered standard errors-based t-statistics inside curly brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. The significance is for double-clustered standard errors-based t-statistics.

Table 7: Stock-Level Regression, Post-1982 period

	(1)	(2)	(3)	(4)	(5)
Age	-0.007	-0.007	-0.003	-0.003	-0.003
	[-32.44]	[-33.06]	[-14.02]	[-12.30]	[-12.35]
	{-5.96}	{-6.49}	{-4.98}	{-4.46}	{-4.48}
	***	***	***	***	***
Size		0.019	0.047	0.017	0.014
		[6.70]	[12.64]	[3.49]	[2.96]
		{1.51}	{2.90}	{0.83}	{0.71}
			***		
B/M			0.043	0.023	0.024
			[4.51]	[2.43]	[2.51]
			{1.34}	{0.77}	{0.79}
Leverage			-0.002	-0.003	-0.003
			[-1.04]	[-1.28]	[-1.27]
			{-0.45}	{-0.57}	{-0.57}
Payout ratio			-0.127	-0.125	-0.123
			[-9.11]	[-8.99]	[-8.84]
			{-8.56}	{-8.47}	{-8.39}
			***	***	***
Earnings variability			1.640	1.511	1.529
			[13.53]	[12.46]	[12.60]
			{7.01}	{6.42}	{6.48}
			***	***	***
Earnings covariability			0.003	0.002	0.002
			[2.87]	[2.43]	[2.46]
			{1.15}	{0.99}	{1.00}
Liquidity beta			-0.126	-0.122	-0.121
			[-4.71]	[-4.57]	[-4.53]
			{-1.05}	{-1.02}	{-1.00}
Bid-ask spread			-4.675	-4.175	-4.274
			[-17.23]	[-15.05]	[-15.42]
			{-1.96}	{-1.76}	{-1.80}
			**	*	*
SE of beta			0.300	0.288	0.289
			[37.37]	[35.86]	[35.99]
			{3.09}	{2.99}	{3.00}
			***	***	***
Number of analysts				0.011	0.011
				[6.40]	[6.45]
				{2.08}	{2.09}
				**	**
Dispersion				2.489	2.518
				[11.69]	[11.83]
				{4.69}	{4.73}
				***	***
Public info				-3.309	
				[-4.13]	
				{-3.74}	
				***	
Private info				-0.780	
				[-1.37]	
				{-2.80}	
				***	
Public info share					-0.022
					[-0.52]
					{-0.40}
N*T	90,745	90,745	89,148	89,148	89,148
Adj R sq	0.011	0.012	0.049	0.053	0.053

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 regression, calculate double-clustered standard errors following Petersen(2009), Cameron, Gelbach, and Miller (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, ordinary t-statistics inside square brackets, and double-clustered standard errors-based t-statistics inside curly brackets. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. The significance is for double-clustered standard errors-based t-statistics.

Table 8: Expected Returns vs. Beta

	(1)	(2)	(3)	(4)
Slope	0.0187	0.0217	0.0369	0.0430
	[1.07]	[1.27]	[2.11]	[3.17]
			**	***
Intercept	0.1383	0.1332	0.1169	0.1106
	[11.61]	[8.23]	[6.83]	[6.47]
	***	***	***	***

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), and age sorted portfolios (columns 3 to 4). 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. The estimated coefficients are annualized by dividing by the annualization factor $\sum_{j=1}^{N} \rho^j$. t-statistics based on Newey-West standard errors are shown inside square brackets. *, **, and *** indicate significance at 10%, 5%, and 1% significance.

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