

The Life Cycle of Beta

Ludwig B. Chincarini
Daehwan Kim
Fabio Moneta*

This version: November 19, 2016.

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. Overall, age is an important conditioning variable to consider when examining the time-variation of beta and the relation between beta and cost of capital.

JEL Classification: G0

Key Words: beta, cost-of-capital, life cycle, CAPM, time-varying beta, determinants of beta

*We would like to thank Wei Du for research assistance and Marlene Haas, Janusz Brzescynski, Jonathan Allen, Fernando Comiran, Tatiana Fedyk, Thomas Grossman, and Nick Tay and participants at the Western Economic Association International Conference for comments. Contact: Ludwig Chincarini, CFA, Ph.D., is a Professor of finance at the University of San Francisco School of Management, Office MH 117, University of San Francisco, School of Management, 2130 Fulton Street, San Francisco, CA 94117. Email: chincarini@hotmail.com or lbchincarini@usfca.edu. Phone: 415-422-6992, Daehwan Kim, Ph.D., Associate Professor in Economics at Konkuk University, Department of Economics, Konkuk University, 1 Hwayang-dong, Gwangjin-gu, Seoul, 143-701, South Korea. Email: dkim@konkuk.ac.kr. Fabio Moneta is an Assistant Professor at Queen's University, Stephen J.R. Smith School of Business, 143 Union Street, Kingston, Ontario, Canada, K7L 3N6. E-mail: fmoneta@business.queensu.ca.

1 Introduction

Despite the criticisms, the Capital Asset Pricing Model (CAPM) is used extensively in finance. The only firm-specific input of 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)); 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. A new, small company, for example, could have low information associated with it, and thus there is large estimation risk (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 company¹, 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 betas increase more for larger positive or negative announcements and for announcements

¹New 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.

²Ball 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.

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 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 opinion. Some studies show that the divergence of stock analyst opinion 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 lifecycle of beta model. That is, new companies

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

⁴For 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. The typical study takes a historical measure of beta for the stock and uses this to measure the excess return of the stock on the day of a news announcement. However, most of these studies fail to account for the fact that the beta of the company actually changes on the day of the announcement. For example, for a new company, especially a small one, a piece of good news presumably raises the stock price on the announcement as well as lowers the beta of the firm. Thus, any measurement of excess returns that does not take this into account might incorrectly measure the excess returns of the security due to the news announcement.

⁵These 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.

can be thought of as having a beta that is composed of an uncertainty piece in addition to the time invariant 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 lifecycle 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 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 20 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.

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 22 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.

There are relevant implications of our findings. First, practitioners that use beta as a measurement for the cost-of-capital or practitioners who use beta as a risk management tool should pay attention to age, as it can improve the beta estimate. Second, researchers who use event studies in finance should pay attention to age. A popular approach for measuring abnormal performance is to compare the performance of a stock against the performance of a benchmark. Especially, when considering long-run performance it is important to understand how the beta changes over time and consider age as an important control for constructing the benchmark.⁷

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; and section 5 concludes.

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

⁷For example, many studies construct a Daniel-Grinblatt-Titman-Wermers (1997) benchmark to adjust for risk. They may wish to add age in the construction of that benchmark. See Kothari and Warner (2007) for a review of long-horizon event studies.

2 The Life Cycle of Beta

2.1 Decomposition of Beta

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

$$r_{i,t} = \alpha_i + \beta_{i,t}r_{m,t} + \epsilon_{i,t} \quad (1)$$

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,

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

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:

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

Given that $z_{i,t}$ has zero mean, we can also show that⁹

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

⁸In the literature the time-varying conditional betas $\beta_{i,t}$ has been commonly model 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).

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

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

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.

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

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

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

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 fundamentals identified by Beaver et al. (1970) such as earnings variability and leverage. It is important then 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. We exclude companies from the financial sectors¹¹ 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 on the exchange) is greater than 22 years.

¹¹In 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.

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

The data cover the period from July 1963 to June 2012. 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. For year t , beta is based on weekly returns from July of year $t-1$ to June of year t . To control for nonsynchronous trading, we adopt the Dimson (1979) technique; we included the lagged market returns as regressors so that our regression equation was

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

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.¹³

3.3 Age Measure

Our measure of age is the number of years since the stock first began trading on the exchange as of June of year t .¹⁴

¹³Thus, our measure is calculated as $SD(\hat{\beta}) = \sqrt{(V(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3))} = \sqrt{(V(\hat{\beta}_1) + V(\hat{\beta}_2) + V(\hat{\beta}_3) + 2Cov(\hat{\beta}_1, \hat{\beta}_2) + 2Cov(\hat{\beta}_2, \hat{\beta}_3) + 2Cov(\hat{\beta}_3, \hat{\beta}_1))}$.

¹⁴Although not reported here, we also considered the year of incorporation as a proxy for age. This alternative measure did not change the main results of the paper.

Our sample begins in 1964 and we consider ages of companies from 0 to 22 years old in every given year. Tables A.1 and A.2 in Appendix A show the age distribution of stocks included in our data set. Over time, the number of public companies and the distribution has changed. In 1964, there were 51 companies that were born (i.e. listed on the stock market in that year), 739 companies that were one year old, and 9 companies that were 22 years old. By 2011, there were 66 new companies born, 29 companies that were 22 years old and the rest of the ages were roughly around 100 companies in each age bracket. One of the largest birth years for companies was 1973 and 1974, when around 1,787 companies existed. This group aged together over time, with some companies dropping off over time to mergers, delistings, etc. Since many stocks enter the sample starting in year 1, rather than year 0, due to our method of constructing age, we chose to drop the year 0 cohort from our analysis.¹⁵

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). 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). That is, 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,

¹⁵This did not affect the qualitative nature of the results.

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 ratios.

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. 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 different size companies. 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 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 divided 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 liquidity of the stocks improves as the firm matures and grows. One may wonder if this 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 a liquidity factor. Our measure is the liquidity beta, which 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 is calculated. 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 multiplying it by -1.

Table 1 reports the summary statistics for our key variables. We average the data over time and cross-sectionally. For the entire sample period, the mean beta is 1.39 and the average company is 8.12 years old. The average company size is 657 million dollars, the average book-to-market ratio is 0.83, the average leverage of the companies is 4.14, the average payout ratio is 30%, the earnings variability is 0.04 and the average earnings covariability is 1.19. The average illiquidity beta is 0.00. The standard error of the beta estimates is 1.30, the average number of analysts following a stock is 3.72, the dispersion of analyst forecasts is 18, 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 stock entered the CRSP database.¹⁶ Between 1964 and 2011, we classified stocks by their age in every year creating age cohorts. Thus, a stock that entered CRSP between July 1, 1970 and June 30, 1971 is part of the 1970 cohort. It's age for the 1970 cohort was zero. We created 23 age-cohort portfolios (Age 0 to Age 22) 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 must 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.

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

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

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} . In order to understand the effect of age on beta, we use three regression methodologies. The first is a

¹⁶In unreported analyses we also looked at other definitions of age, including incorporation date and IPO dates with similar results.

pooled regression, whereby we take all observations from every year in our sample with betas and corresponding independent variables and run one regression. This naturally ignores any time variation on this relationship.

The second is a Fama-MacBeth regression. Each year we run a cross-sectional regression, estimate the parameters, and then average the parameters over all of the years. The third is a between estimation. We first average the variables across years (i.e. beta and age and \mathbf{X}) and then run a cross-sectional regression of beta against age.

4.2 Age, Fundamentals, Uncertainty, and Beta

In order to untangle the different sources influencing beta, we consider 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 about -0.019. Thus, every 10 years of life, portfolio beta declines by 0.20 points. For a company with an initial beta of 1.40, this amounts to a 14% decline over ten years. In other specifications, as shown in Figure 1, beta declines by about 0.17 in 10 years. This decline is depicted in figure as the average beta declines from approximately 1.43 to 1.09 over 20 years. In an unreported regression, we note that size alone is significant in determining the

beta of a company. However, once we consider age, size appears to be insignificant as does book-to-market, leverage, the payout ratio, earnings covariability, and the standard error of beta. The liquidity beta and the earnings variability are the only other variables significant in determining the beta of a company. This makes sense, since a higher variability in earnings reflects higher uncertainty in the company and could lead to a higher beta for reasons discussed earlier. Liquidity beta also makes sense since higher illiquidity in a stock would presumably lead to a higher beta. A positive and significant correlation between earnings variability and beta was also documented by Beaver et al. (1970), however neither fundamental factors or most uncertainty measures are able to capture the effect of declining beta with age. The coefficient on age is instead stable across the different specifications. Hence, age seems to be a very important and novel factor determining beta.

[INSERT FIGURE 1 ABOUT HERE]

In Table 3, we also show the Fama-MacBeth and Between estimation 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 and Between estimation specifications.

[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 2. 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 are insignificant in explaining beta, when age is included in the regressions.¹⁷

[INSERT FIGURE 2 ABOUT HERE]

4.3 Information and Beta

In the previous section, we showed that the primary driver of declining beta is age, not fundamental variables or certain proxies for uncertainty of beta. In this section, we consider information variables. That is, if there is a little information on a particular company, this may drive beta higher. As more information become available on a company, then beta might be lower in equilibrium. Our information variables do not go back to 1964, 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) shows the results of a regressions of beta on age, fundamentals, uncertainty, and the new information factors.

[INSERT TABLE 4 ABOUT HERE]

¹⁷We 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.

The earlier results remain qualitatively the same in the period from 1982 to 2011; age still influences beta. However, size has now some explanatory power in explaining beta and both earnings variability and liquidity beta continue to have a significant role in explaining beta. The number of analysts and the dispersion of analyst forecasts do not affect the beta in either specifications of the regression shown in the table. Neither the precision of public or private information statistically affects beta. However, the precision of public information has a negative coefficient, indicating that as the precision of public information increases, beta declines. This makes sense, but it is not statistically significant.

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.

4.4 Leverage and Beta

Basic fundamental factors do not seem 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). Thus, 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.

$$\beta_t = \beta_{60} \frac{(1 + L_t)}{(1 + L_{60})} \quad (8)$$

where β_t is our measure of unlevered beta, β_{60} 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_{60} is the average of the leverage ratios over the estimation period for the unadjusted beta.¹⁸ Because of data errors or otherwise, we winsorize all values of $\frac{(1+L_t)}{(1+L_{60})}$ 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 Information Announcements

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 CAPM holding on announcement days but not on non-announcement days. Previously, we documented that beta declines over age partly explained by a reduction in firm-specific

¹⁸Our measured beta is measured from July to June data, thus, L_{60} is set to be the leverage of the end of December each year, while the latest leverage, L_t is measured as of the end of June each year. For stocks whose fiscal year ends in December, we take the exact leverage ratio and not a weighted average, and for stocks whose fiscal year ends in June, we take the exact leverage ratio, not a weighted average.

uncertainty. If it is actually firm-specific information that affects the beta and generates its reduction over time, we should then expect that this effect is stronger for non-announcement days. Indeed, during announcement days beta should better capture economic-wide shocks, whereas during non-announcement days, firm-specific information should be more important for the determination of beta.

To test whether the decline of beta over age is indeed stronger during non-announcement days, every year we estimated the beta of each stock separately for announcement days and for non-announcement days. Table 6 reports the results for various specifications on announcement and non-announcement days. Consistent with our prediction we see that the estimated coefficient on age is approximately 10% to 36% larger in absolute value when we use betas estimated during non-announcement days with a regression of beta on age. Table 7 shows the test statistics for the difference in estimated coefficients on age during announcement and non-announcement days. In the age-only specification, the difference between the two coefficients is statistically significant with a p-value of 3%. When we consider more control variables, this difference diminishes. On non-announcement days, earnings variability becomes more important in explaining the behavior on beta, which makes sense. Thus, although the uncertainty measures as proxied by earnings variability appear to explain the more severe decline in beta during non-announcement days than announcement days, these variables are not able to explain the decline in beta that occurs during all days.

[INSERT TABLE 6 ABOUT HERE]

[INSERT TABLE 7 ABOUT HERE]

4.6 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 perform 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-firm variation in age and other explanatory variables. The results are shown in Tables 8 for the 1961-2011 sample period and 9 for the 1982-2011 sample period.

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, including earnings variability and covariability, the standard error of beta, size and BM are significant, as well as illiquidity. Despite the additional variables appearing statistically significant in a way we would expect, age is still significant and its point estimate is larger when the other variables are included.

[INSERT TABLE 8 ABOUT HERE]

[INSERT TABLE 9 ABOUT HERE]

5 Conclusion

Measuring beta accurately is important for understanding securities markets. There has been numerous research 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 10-year period is 0.20.

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 becomes irrelevant. 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.

5.1 Figures

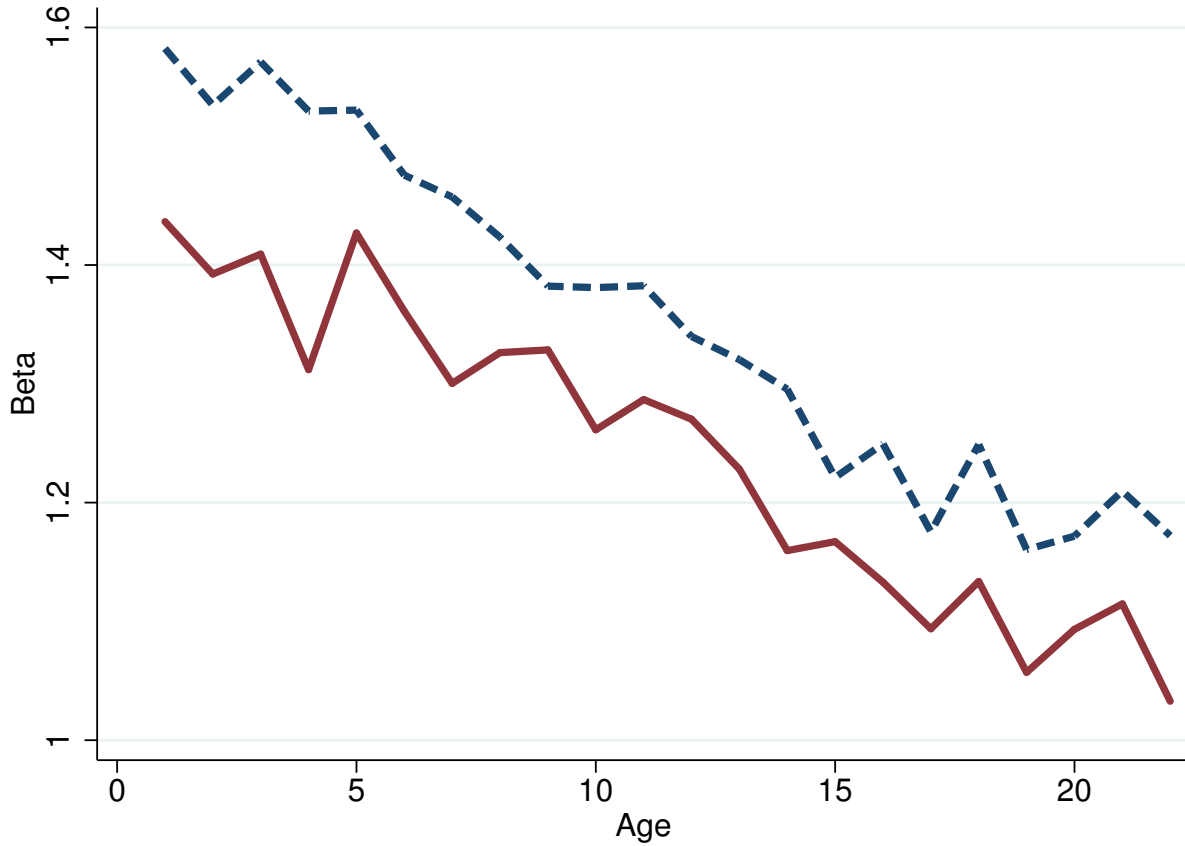


Figure 1: The Decline of Beta with Age

Note: The figure plots beta against age (expressed in years). The solid line represents value-weighted beta, and the dotted line equal-weighted beta. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $\lfloor d/365 \rfloor$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $\lfloor x \rfloor$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; 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. We then take average of these values across years holding age fixed. The figure plots these averages.

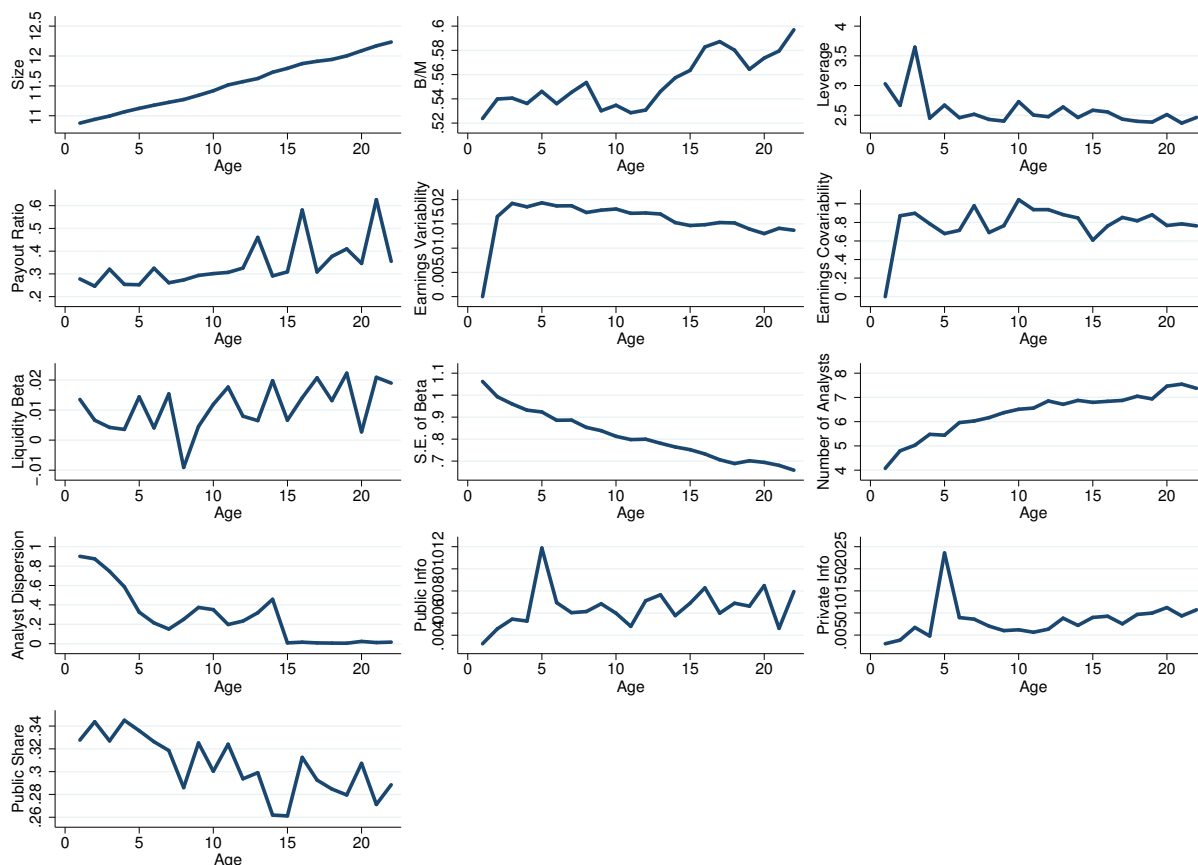


Figure 2: Other Variables with Age

Note: The figure plots size and other variables against age (expressed in years). See the notes to Table 1 for description of each variable. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . For each portfolio, we have calculated equal-weighted average of each variable. We then take average of these values across years holding age fixed. The figure plots these averages.

5.2 Tables

Table 1: Summary Statistics

Variable	Obs	Mean	SD	Min	Median	Max
Beta	133,403	1.39	1.62	-35.26	1.27	43.14
Age	133,403	8.12	5.85	1.00	7.00	22.00
Market cap	133,403	656.91	5313.48	0.34	61.94	463699.75
B/M	117,890	0.83	1.30	0	0.60	208.36
Leverage	117,511	4.14	261.88	0.99	1.86	87702.50
Payout ratio	90,822	0.30	4.15	-0.04	0.00	774.15
Earnings variability	88,514	0.04	0.10	0	0.02	11.02
Earnings covariability	88,514	1.19	14.80	-2404.80	0.38	408.05
Liquidity beta	133,403	0.00	0.38	-17.17	0.00	18.23
SE of beta	133,403	1.30	0.90	0.04	1.08	25.63
Number of analysts	62,611	3.72	4.45	0	2.08	39.33
Dispersion	47,298	17.74	1746.80	0	0	343781.09
Public info	12,991	0.01	0.02	0	0	0.70
Private info	12,991	0.01	0.04	0	0	1.74
Public info share	12,991	0.65	0.26	0	0.70	1.00

Note: The sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have calculated the following variables for each stock-year. **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 . **Age** (expressed in years) is determined as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . **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 ratios. 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 is calculated. 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 multiplying it by -1. **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 as reported in the IBES monthly files 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 (dispersion), 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 (1964-2011)

	(1)	(2)	(3)
Age	-0.019 [-11.65] ***	-0.020 [-10.88] ***	-0.020 [-10.19] ***
Size		0.013 [1.02]	0.009 [0.71]
B/M			0.016 [0.33]
Leverage			-0.002 [-0.33]
Payout ratio			-0.007 [-0.47]
Earnings variability			2.289 [2.04] **
Earnings covariability			0.013 [1.23]
Liquidity beta			0.287 [2.36] **
SE of beta			-0.015 [-0.41]
N*T	1,054	1,054	1,054
Adj R sq	0.113	0.113	0.125

Note: The table reports on the regressions of beta on age and other variables. The regressions are carried out for year-age portfolios. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $\lfloor d/365 \rfloor$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $\lfloor x \rfloor$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . For each portfolio, we have calculated beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, 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 size of a stock is the logarithm of its market capitalization. For other variables, see Table 1 for further description. The table reports the coefficient estimates and the associated t-statistics (inside brackets) from the ordinary least square estimation. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. The estimation includes a constant term and a dummy variable indicating whether earnings variability and covariability are missing. (These variable are missing if there are less than 3 stocks in the portfolio with non-missing values. When these variables are missing, we set the value to be zero.)

Table 3: Portfolio-Level Regression: Panel Estimation (1964-2011)

	FM		Between	
	(1)	(2)	(3)	(4)
Age	-0.019 [-6.77] ***	-0.014 [-4.42] ***	-0.019 [-15.95] ***	0.007 [0.32]
Size		-0.010 [-0.32]		-0.402 [-1.15]
T	48	48		
N			22	22
Adj R sq			0.923	0.925

Note: The table reports on the regressions of beta on age and other variables. The regressions are carried out for year-age portfolios. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . For each portfolio, we have calculated beta as the value-weighted average of the beta of individual stocks. The size of the portfolio is the equal-weighted average of individual stocks' size (the logarithm of the market capitalization). See Table 1 for further description of variables. The table reports the coefficient estimates and the associated t-statistics (inside brackets) from the Fama-MacBeth (FM) estimation and the between estimation. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. The FM estimation has two steps. 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. The between estimation also has two steps. In the first step, we take the average of each variable across different years, holding the age fixed. The resulting data set has one observation per age. In the second step, we run regressions using this data set.

Table 4: Portfolio-Level Regression (1982-2011)

	(1)	(2)	(3)	(4)	(5)
Age	-0.015 [-7.04] ***	-0.017 [-7.81] ***	-0.017 [-6.89] ***	-0.016 [-6.33] ***	-0.016 [-6.14] ***
Size		0.058 [3.55] ***	0.055 [3.20] ***	0.050 [2.30] **	0.044 [2.05] **
B/M			0.030 [0.45]	0.038 [0.52]	0.060 [0.83]
Leverage			-0.002 [-0.29]	-0.001 [-0.27]	-0.001 [-0.24]
Payout ratio			-0.003 [-0.18]	-0.006 [-0.36]	-0.005 [-0.30]
Earnings variability			3.022 [2.03] **	3.111 [2.05] **	3.300 [2.19] **
Earnings covariability			0.011 [0.83]	0.010 [0.73]	0.009 [0.71]
Liquidity beta			0.314 [2.43] **	0.357 [2.62] ***	0.377 [2.78] ***
SE of beta			-0.018 [-0.43]		
Number of analysts				0.002 [0.43]	0.002 [0.53]
Dispersion				0.004 [0.74]	0.004 [0.78]
Public info				-1.528 [-1.11]	
Private info				-0.035 [-0.05]	
Public info share					0.027 [0.23]
N*T	660	660	660	660	660
Adj R sq	0.069	0.085	0.096	0.101	0.098

Note: The table reports on the regressions of beta on age and other variables. The regressions are carried out for year-age portfolios for the period between 1982 and 2011. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . For each portfolio, we have calculated the beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, standard error of beta, 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. The size of a stock is the logarithm of its market capitalization. For other variables, see Table 1 for further description. The table reports the coefficient estimates and the associated t-statistics (inside brackets) from the ordinary least square estimation. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. The estimation includes a constant term and three dummy variables indicating the missing values of earnings variability and covariability, of analysts and dispersion, and of public and private info. (These variable are missing if there are less than 3 stocks in the portfolio with non-missing values. When these variables are missing, we set the value to be zero.)

Table 5: Portfolio-Level Regression: Unlevered Beta (1964-2011)

	(1)	(2)	(3)
Age	-0.020 [-11.85] ***	-0.021 [-11.27] ***	-0.022 [-10.48] ***
Size		0.019 [1.49]	0.016 [1.17]
B/M			0.018 [0.37]
Leverage			-0.001 [-0.30]
Payout ratio			-0.005 [-0.33]
Earnings variability			2.073 [1.81] *
Earnings covariability			0.013 [1.25]
Liquidity beta			0.265 [2.13] **
SE of beta			-0.004 [-0.10]
N*T	1,054	1,054	1,054
Adj R sq	0.117	0.118	0.128

Note: The table reports on the regressions of the unlevered beta on age and other variables. The regressions are carried out for year-age portfolios. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . For each portfolio, we have calculated the unlevered beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, 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 $\frac{(1+L_t)}{(1+L_{60})}$ where L_t is the most recent leverage (i.e. debt-to-equity) ratio of the company, and L_{60} is the average of the leverage ratios over the estimation period for the original beta. The size of a stock is the logarithm of its market capitalization. For other variables, see Table 1 for further description. The table reports the coefficient estimates and the associated t-statistics (inside brackets) from the ordinary least square estimation. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. The estimation includes a constant term and a dummy variable indicating whether earnings variability and covariability are missing. (These variable are missing if there are less than 3 stocks in the portfolio with non-missing values. When these variables are missing, we set the value to be zero.)

Table 6: Portfolio-Level Regression: Announcement-Day Beta vs. Non-announcement-day Beta (1980-2011)

	Announcement-day beta			Non-announcement-day beta		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.011 [-6.33] ***	-0.010 [-5.36] ***	-0.009 [-4.63] ***	-0.015 [-7.66] ***	-0.013 [-6.09] ***	-0.010 [-4.10] ***
Size		-0.026 [-1.10]	-0.017 [-0.70]		-0.067 [-2.36] **	-0.070 [-2.43] **
B/M			0.050 [1.01]			-0.139 [-2.38] **
Leverage			-0.001 [-0.36]			0.004 [0.92]
Payout ratio			0.007 [0.56]			0.013 [0.85]
Earnings variability			1.293 [1.07]			4.365 [3.06] ***
Earnings covariability			0.001 [0.13]			-0.008 [-0.67]
liquidity beta			0.074 [0.85]			0.018 [0.17]
SE of beta			0.093 [2.73] ***			0.178 [4.47] ***
N*T	677	677	677	677	677	677
Adj R sq	0.055	0.055	0.062	0.079	0.085	0.132

Note: The table reports on the regressions of the announcement-day and non-announcement-day beta on age and other variables. The regressions are carried out for year-age portfolios. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 22 age portfolios corresponding to ages between year 1 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . For each portfolio, we have calculated the unlevered beta, size, B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, 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. Announcement-day beta is estimated using only announcement-days. A trading day is an announcement day if there is a release of at least one of the following macro variables: retail sales, business inventories, non-farm payrolls, Chicago purchasing manager index, consumer confidence, consumer price index, durable good orders, employment cost index, existing home sales, Federal Open Market Committee rate decision, GDP, GDP price deflator, housing starts, industrial production, initial jobless claims, leading indicators, monthly Treasury budget statement, ISM Purchasing Managers' Index, new home sales, Philadelphia Fed index, producer price index, and unemployment rate. Non-announcement-day beta is estimated excluding announcement-days. The size of a stock is the logarithm of its market capitalization. For other variables, see Table 1 for further description. The table reports the coefficient estimates and the associated t-statistics (inside brackets) from the ordinary least square estimation. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. The estimation includes a constant term and a dummy variable indicating whether earnings variability and covariability are missing. (These variable are missing if there are less than 3 stocks in the portfolio with non-missing values. When these variables are missing, we set the value to be zero.)

Table 7: Test of Difference Between Announcement- and Non-announcement-day Betas

	(1)	(2)	(3)
Age	0.005 {0.03} **	0.004 {0.14}	0.000 {0.87}
Size		0.041 {0.17}	0.052 {0.09} *
B/M			0.189 {0.00} ***
Leverage			-0.006 {0.25}
Payout ratio			-0.006 {0.73}
Earnings variability			-3.072 {0.05} **
Earnings covariability			0.010 {0.47}
liquidity beta			0.056 {0.61}
SE of beta			-0.086 {0.05} **

Note: The table reports the tests of the difference between two sets of coefficient estimates reported in Table 6, i.e. estimates for announcement day beta and estimates for non-announcement-day beta. Difference between two corresponding coefficient estimates is followed by p-values inside curly brackets. P-values are from F tests applied seeming unrelated regressions. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively.

Table 8: Stock-Level Regression–Fixed Effect Estimation (1964-2011)

	(1)	(2)	(3)
Age	-0.017 [-18.89] ***	-0.020 [-18.80] ***	-0.022 [-18.81] ***
Size		0.026 [4.58] ***	0.102 [16.36] ***
B/M			0.016 [3.73] ***
Leverage			0.000 [0.13]
Payout ratio			0.000 [-0.21]
Earnings variability			0.323 [5.61] ***
Earnings covariability			0.001 [3.78] ***
Liquidity beta			0.077 [7.08] ***
SE of beta			0.408 [57.91] ***
N*T	133,403	133,403	133,403
Adj R sq	0.053	0.053	0.079

Note: The table reports on the regressions of beta on age and other variables. The regressions are carried out for individual stocks. The sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is between year 1 and 22. See Table 1 for description of variables. The table reports the coefficient estimates and the associated t-statistics (inside brackets) from the fixed-effect estimation. *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. Each variable is "de-meaned" –i.e. the average for each stock is subtracted–before estimation is carried out. The estimation includes year dummy variables and dummy variables indicating the missing values of B/M, leverage, payout ratio, earnings variability, earnings covariability, and liquidity beta. When these variables are missing, we set the values to be zero.

Table 9: Stock-Level Regression–Fixed Effect Estimation (1982-2011)

	(1)	(2)	(3)	(4)	(5)
Age	-0.003 [-1.89] *	-0.003 [-2.18] **	-0.006 [-3.49] ***	-0.006 [-3.64] ***	-0.006 [-3.64] ***
Size		0.008 [1.13]	0.098 [12.27] ***	0.078 [9.12] ***	0.077 [9.02] ***
B/M			0.012 [2.45] **	0.010 [1.97] **	0.010 [1.94] *
Leverage			0.000 [0.08]	0.000 [0.07]	0.000 [0.06]
Payout ratio			0.000 [0.21]	0.000 [0.14]	0.000 [0.15]
Earnings variability			0.362 [5.34] ***	0.372 [5.48] ***	0.373 [5.51] ***
Earnings covariability			0.002 [3.66] ***	0.002 [3.65] ***	0.002 [3.66] ***
Liquidity beta			0.066 [5.40] ***	0.066 [5.41] ***	0.066 [5.42] ***
SE of beta			0.401 [49.20] ***		
Number of analysts				0.004 [1.50]	0.004 [1.55]
Dispersion				0.000 [-1.25]	0.000 [-1.25]
Public info				-1.980 [-2.44] **	
Private info				-0.007 [-0.02]	
Public info share					-0.049 [-0.92]
N*T	94,983	94,983	94,983	94,983	94,983
Adj R sq	0.048	0.048	0.075	0.075	0.075

Note: The table reports on the regressions of beta on age and other variables. The regressions are carried out for individual stocks, for the period from 1982 to 2011. The initial sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is 22 or less. See Table 1 for description of variables. The table reports the coefficient estimates and the associated t-statistics (inside brackets) *, **, and *** represent significance at the 10%, 5%, and 1% confidence intervals, respectively. from the fixed-effect estimation. Each variable is "de-measured"—i.e. the average for each stock is subtracted—before estimation is carried out. The estimation includes year dummy variables and dummy variables indicating the missing values of B/M, leverage, payout ratio, earnings variability, earnings covariability, liquidity beta, number of analysts, dispersion, public info, private info, and public info share. When these variables are missing, we set the values to be zero.

A Appendix A: Age Distribution Tables

Table A.1: Age Distribution of Companies I

Year	Age											
	0	1	2	3	4	5	6	7	8	9	10	11
1964	51	739	44	42	43	25	24	27	16	17	6	20
1965	52	118	710	43	41	43	26	24	24	16	16	6
1966	58	108	111	680	41	39	39	25	24	23	16	15
1967	53	98	103	104	639	38	37	38	24	23	22	14
1968	74	105	93	94	94	593	37	34	34	23	23	21
1969	71	139	100	86	92	89	558	36	32	31	23	23
1970	88	167	135	95	82	88	87	530	33	32	30	22
1971	61	155	163	131	93	79	83	81	503	31	32	27
1972	77	122	153	163	126	92	76	80	80	480	31	32
1973	856	139	117	144	153	121	88	73	79	77	450	31
1974	36	1787	129	109	133	147	119	84	70	76	76	410
1975	13	64	1495	126	105	127	147	120	84	67	72	72
1976	32	49	64	1475	120	107	123	143	113	82	65	70
1977	37	86	53	58	1416	112	100	118	135	105	75	65
1978	23	106	85	47	60	1360	103	89	117	126	99	71
1979	50	83	99	90	46	55	1322	91	87	114	122	99
1980	49	136	81	94	79	42	55	1246	90	78	109	118
1981	159	198	134	81	93	80	44	55	1281	82	74	100
1982	141	350	157	105	70	80	77	43	52	1166	79	67
1983	119	265	360	154	109	70	74	73	41	54	1150	77
1984	311	348	233	316	128	96	60	66	68	42	48	1100
1985	117	544	301	189	253	105	86	53	59	61	31	45
1986	167	248	488	284	169	234	100	85	44	55	56	26
1987	254	422	211	432	253	153	211	92	80	41	51	46
1988	178	467	344	166	367	222	131	182	78	74	39	49
1989	115	260	398	285	149	316	192	113	167	66	60	32
1990	119	210	218	358	253	132	278	164	108	142	51	51
1991	88	244	177	197	322	229	115	252	151	102	132	46
1992	214	247	223	157	199	310	229	113	251	142	95	134
1993	216	515	237	222	158	198	313	233	110	242	146	96
1994	393	463	467	210	199	140	194	301	220	105	225	138
1995	231	662	404	429	187	181	133	177	286	205	101	219
1996	354	460	610	376	392	178	169	131	169	257	187	98
1997	396	712	393	539	339	348	153	150	115	156	229	170
1998	314	577	605	343	463	304	319	137	144	99	144	205
1999	114	499	488	496	282	384	262	262	124	121	86	125
2000	303	303	418	412	412	225	332	236	238	109	104	81
2001	192	416	206	323	303	327	184	270	191	201	100	89
2002	53	190	315	167	259	238	264	156	233	167	174	82
2003	36	107	175	295	145	245	224	248	143	218	161	163
2004	84	70	97	165	273	136	221	208	248	132	204	147
2005	105	175	63	86	149	250	116	202	194	230	117	188
2006	117	180	164	60	74	142	228	105	187	179	213	108
2007	105	224	158	150	57	67	126	202	101	176	164	191
2008	129	217	192	132	118	50	63	108	171	91	157	141
2009	35	163	168	149	106	93	42	59	83	136	77	134
2010	76	54	132	155	147	104	97	40	59	87	140	75
2011	66	140	45	117	141	134	94	88	38	53	85	132

Note: The sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is 22 or less. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 23 age portfolios corresponding to ages between 0 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . The table shows the number of stock-years included in each portfolio.

Table A.2: Age Distribution of Companies II

Year	Age										
	12	13	14	15	16	17	18	19	20	21	22
1964	13	26	19	16	28	38	35	24	18	1	9
1965	19	13	26	20	16	28	37	34	25	17	1
1966	6	19	13	26	20	16	27	37	33	22	17
1967	15	6	18	11	24	19	15	27	36	33	22
1968	14	13	6	16	11	24	18	14	22	33	30
1969	19	13	13	6	16	10	24	18	13	21	31
1970	23	18	13	13	6	16	10	24	18	13	20
1971	22	22	16	13	13	6	16	10	24	18	13
1972	27	22	22	16	12	12	6	16	9	24	18
1973	31	27	21	22	16	12	12	6	16	9	23
1974	30	31	25	22	22	17	12	12	6	15	9
1975	398	29	31	26	21	22	17	12	12	6	15
1976	67	387	29	30	25	21	21	15	12	12	6
1977	66	63	378	29	30	24	21	20	14	12	12
1978	63	62	61	364	28	30	23	19	20	14	12
1979	70	58	58	62	351	26	29	20	18	19	12
1980	92	67	55	54	57	326	24	29	20	18	17
1981	107	88	63	53	49	53	310	24	29	19	17
1982	90	102	75	58	51	46	50	287	22	26	19
1983	66	88	95	73	56	47	48	47	285	22	24
1984	73	60	80	93	73	54	45	43	46	269	19
1985	1001	67	54	77	76	69	48	39	42	44	247
1986	42	933	64	51	74	75	65	48	37	39	41
1987	26	36	860	60	47	68	73	61	42	34	33
1988	41	24	31	789	52	44	60	66	59	36	29
1989	45	39	21	26	717	50	38	53	59	52	35
1990	29	46	33	17	24	665	49	36	52	55	46
1991	46	29	45	34	15	23	618	45	35	50	51
1992	46	42	28	44	31	15	21	608	45	33	48
1993	136	59	43	27	45	30	16	22	599	46	32
1994	92	126	57	43	27	42	30	16	20	578	46
1995	133	83	114	50	44	27	38	31	17	17	551
1996	215	122	77	115	53	45	24	36	29	14	18
1997	87	202	109	70	108	45	38	24	34	28	14
1998	146	81	185	106	62	97	39	34	22	29	25
1999	187	131	74	163	99	59	80	36	30	21	26
2000	116	163	117	65	141	88	53	74	27	27	19
2001	65	97	144	95	62	124	70	44	69	26	24
2002	79	56	82	120	85	56	111	66	35	61	23
2003	81	75	55	77	120	81	50	105	66	35	59
2004	155	76	76	56	71	109	76	44	105	60	38
2005	140	144	71	74	45	65	102	70	43	100	57
2006	181	133	133	66	69	44	62	98	63	41	96
2007	96	167	124	125	58	66	41	55	91	58	37
2008	160	80	148	115	108	59	58	39	48	79	58
2009	129	145	74	131	104	98	50	49	32	46	69
2010	138	123	139	72	127	101	94	48	46	31	45
2011	65	128	115	133	71	116	99	93	47	42	29

Note: The sample includes stock-years, between 1964 and 2011 of non-financial common stocks in the CRSP universe, for which i) price is above \$1, ii) at least 27 weekly returns are available between July of year $t-1$ and June of year t , and iii) age is 22 or less. We have determined the age of a stock-year as $[d/365]$ where d is the number of days between the stock's first quote date in CRSP and June 30 of year t , and $[x]$ is the largest integer less than or equal to x . We have sorted the stock-years of year t into 23 age portfolios corresponding to ages between 0 and 22; i.e., portfolio (t, a) includes stock-years of year t and age a . The table shows the number of stock-years included in each portfolio.

References

- [1] AMIHUD, YAKOV. “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects”. *Journal of Financial Markets*, 5:31–56, 2002.
- [2] AMIHUD, YAKOV, AND HAIM MENDELSON. “The Liquidity Route to a Lower Cost of Capital”. *Journal of Applied Corporate Finance*, 12:8–25, 2000.
- [3] ANDERSON, ANNE-MARIE, AND EDWARD A. DYL. “Market Structure and Trading Volume”. *The Journal of Financial Research*, 28:115–131, March 2005.
- [4] ANDERSON, EVAN W., ERIC GHYSELS, AND JENNIFER JUERGENS. “Do Heterogeneous Beliefs Matter for Asset Pricing?”. *The Review of Financial Studies*, pages 875–924, May 25 2005.
- [5] ARMSTRONG, CHRISTOPHER S., BANERJEE, SNEHAL, AND CARLOS CORONA. “Factor-Loading Uncertainty and Expected Returns”. *The Review of Financial Studies*, 26:158–207, January 2013.
- [6] BALL, RAY AND S.P. KOTHARI. “Security Returns around Earnings Announcements”. *The Accounting Review*, pages 718–738, October 1991.
- [7] BANZ, ROLF W. “The Relationship Between Return and Market Value of Common Stocks”. *Journal of Financial Economics*, 9:3–18, March 1981.
- [8] BARRON, ORIE E., KIM, OLIVER, LIM, STEVE C., AND DOUGLAS E. STEVENS. “Using Analysts’ Forecasts to Measure Properties of Analysts’ Information Environment”. *The Accounting Review*, October 1998.
- [9] BARRY, CHRISTOPHER B. “Effects of Uncertain and Nonstationary Parameters Upon Capital Market Equilibrium Conditions”. *The Journal of Financial and Quantitative Analysis*, 13:419–433, September 1978.
- [10] BARRY, CHRISTOPHER B., AND STEPHEN J. BROWN. “Differential Information and Security Market Equilibrium”. *The Journal of Financial and Quantitative Analysis*, 20:407–422, December 1985.
- [11] BEAVER, WILLIAM, KETTLER, PAUL, AND MYRON SCHOLES. “The Association between Market Determined and Accounting Determined Risk Measures”. *The Accounting Review*, 45:654–682, October 1970.
- [12] BLUME, M. “Betas and Their Regression Tendencies”. *Journal of Finance*, 30:785–795, June 1975.
- [13] BLUME, MARSHALL E. “Portfolio Theory: A Step Toward Its Practical Application”. *The Journal of Business*, 43:152–173, April 1970.
- [14] BOTOSAN, CHRISTINE, PLUMLEE, MARLENE, AND YUAN XIE. “The Role of Information Precision in Determining the Cost of Equity Capital”. *Review of Financial Studies*, 9:233–259, 2004.
- [15] BREEN, WILLIAM J., GLOSTEN, LARRY R., AND RAVI JAGANNATHAN. “Economic Significance of Predictable Variations in Stock Index Returns”. *The Journal of Finance*, pages 1177–1190, 1989.

- [16] CHEN, NAI-FU. “Financial Investment Opportunities and the Macroeconomy”. *The Journal of Finance*, pages 529–554, 1991.
- [17] CLARKSON, PETER MACKAY. “Capital Market Equilibrium and Differential Information: An Analytical and Empirical Investigation”. *Unpublished Ph.D. Dissertation, University of British Columbia*, October 1986.
- [18] CLARKSON, PETER M. AND REX THOMPSON. “Empirical Estimates of Beta When Investors Face Estimation Risk”. *The Journal of Finance*, 45:431–453, June 1990.
- [19] COLES, JEFFREY L., AND URI LOEWENSTEIN. “Equilibrium Pricing and Portfolio Composition in the Presence of Uncertain Parameters”. *Journal of Financial Economics*, 22:279–303, December 1988.
- [20] DANIEL, KEN, GRINBLATT, MARK, TITMAN, SHERIDAN, AND RUSS WERMERS. “Measuring Mutual Fund Performance with Characteristic-Based Benchmarks”. *The Journal of Finance*, 52:1035–1058, July 1997.
- [21] DIETHER, KARL B., MALLOY, CHRISTOPHER J., AND ANNA SCHERBINA. “Differences of Opinion and the Cross Section of Stock Returns”. *The Journal of Finance*, pages 2113–2141, October 2002.
- [22] DIMSON, ELROY. “Risk Measurement when Shares are Subject to Infrequent Trading”. *Journal of Financial Economics*, 7:197–226, June 1979.
- [23] DOUKAS, JOHN A., CHANSOG KIM, AND CRISTOS PANTZALIS. “Divergence of Opinion and Equity Returns”. *Journal of Financial and Quantitative Analysis*, pages 573–606, September 2006.
- [24] EASLEY, DAVID, AND MAUREEN O’HARA. “Information and the Cost of Capital”. *The Journal of Finance*, 59:1553–1583, August 2004.
- [25] FAMA, EUGENE F. AND KENNETH R. FRENCH. “Business Conditions and the Expected Returns on Bonds and Stocks”. *Journal of Financial Economics*, pages 23–50, 1989.
- [26] FAMA, EUGENE F. AND KENNETH R. FRENCH. “The Cross-Section of Expected Stock Returns”. *The Journal of Finance*, pages 427–466, 1992.
- [27] FAMA, EUGENE F. AND KENNETH R. FRENCH. “Common Risk Factors in the Returns on Bonds and Stocks”. *Journal of Financial Economics*, pages 3–56, 1993.
- [28] FERSON, WAYNE E. AND CAMPBELL R. HARVEY. “The Variation of Economic Risk Premiums”. *Journal of Political Economy*, pages 385–415, 1991.
- [29] GHYSELS, ERIC. “On Stable Factor Structures in the Pricing of Risk: Do Time-Varying Betas Help or Hurt?”. *The Journal of Finance*, 2:549–573, April 1998.
- [30] HANDA, PUNEET, AND SCOTT C. LINN. “Arbitrage Pricing with Estimation Risk”. *The Journal of Financial and Quantitative Analysis*, 28:81–100, March 1993.
- [31] JAGANNATHAN, RAVI AND ZHENYU WANG. “The Conditional CAPM and the Cross-Section of Expected Returns”. *The Journal of Finance*, March 1996.
- [32] KEIM, DONALD B. AND ROBERT F. STAMBAUGH. “Predicting Returns in the Stock and Bond Markets”. *Journal of Financial Economics*, pages 357–390, 1986.

- [33] KHOTARI, S.P. AND JEROLD B. WARNER. “Econometrics of Event Studies”. *Handbook of Corporate Finance: Empirical Corporate Finance, Volume A*, 1, 2006.
- [34] KOGAN, LEONID AND TAN WANG. “A Simple Theory of Asset Pricing under Model Uncertainty”. *Unpublished Manuscript*, pages 1–29, 2003.
- [35] KUMAR, PRAVEEN, SORESCU, SORIN M., BOEHME, RODNEY D., AND BARTLEY R. DANIELSON. “Estimation Risk, Information, and the Conditional CAPM: Theory and Evidence”. *The Review of Financial Studies*, 21:1037–1075, May 2008.
- [36] LAMBERT, RICHARD, LEUZ, CHRISTIAN, AND ROBERT E. VERRECCHIA. “Accounting Information, Disclosure, and the Cost of Capital”. *Journal of Accounting Research*, 45:385–420, May 2007.
- [37] PASTOR, LUBOS, AND ROBERT F. STAMBAUGH. “Liquidity Risk and Expected Stock Returns”. *The Journal of Political Economy*, 111:642–685, June 2003.
- [38] PATTON, ANDREW J. AND MICHELA VERARDO. “Does Beta Move with News? Firm-Specific Information Flows and Learning about Profitability”. *The Review of Financial Studies*, pages 1–51, July 3 2012.
- [39] REINGANUM, MARC R., AND JANET KIHOLM SMITH. “Investor Preference for Large Firms: New Evidence on Economies of Size”. *The Journal of Industrial Economics*, 32:213–227, December 1983.
- [40] SAVOR, PAVEL, AND MUNGO WILSON. “Asset Pricing: A Tale of Two Days”. *Journal of Financial Economics*, 113:171–201, August 2014.
- [41] WILLIAMS, JOSEPH T. “Capital Asset Prices with Heterogeneous Beliefs”. *Journal of Financial Economics*, 5:219–239, November 1977.