The Cost of Equity Capital for Unlisted Firms

Evidence From USA Data

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Submitted in December of 2013 to fulfil the requirements of Doctor of Philosophy

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LIST OF ABBREVIATIONS

ABS	Absolute value
BACC	Accounting beta
BD	Book value of debt
BE	Book value of equity
BE	Book value of equity
BMKT	Sharpe-Lintner CAPM beta
BOP	Operational beta
Bu	Unlevered beta
CAPM	Sharp-Lintner capital asset pricing model
CF	Cash flow
CFCE	Operating cash flow to equity ratio
CFTA	Operating cash flow to assets Ratio
Cov	covariance
CRSP	Center for research in security prices
d	Lagged variation
D	Market value of debt
DFL	Degree of financial leverage
DOL	Degree of operating leverage
DR	Discount rate
E	Market value of equity
E	Market value of equity
EBCE	EBITDA to equity ratio
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciations and Amortizations
EBTA	EBITDA to assets ratio
EL	Market value of levered common equity
Eu	Expected market value of unlevered common equity
GDP	Gross domestic product
GRWT	Growth
IRR	Internal rate of return
Kd	Cost of debt
Ke	Cost of equity capital
log	Logarithm
max	Maximum
ME	Miles and Ezzell
min	Minimum
MM	Modigliani and Miller
MTBM	Modified two–beta model
N	News
NI	Net income
OICE	EBIT to equity ratio
OITA	EBIT to assets ratio
p	Probability
p25	25% quantil
p25	75% quantil
p50	Median
PE	Private equity
PE	Private equity
PLB	Proxy Levered Beta
RA	Accounting Return
ROA	Net income to assets ratio
ROE	Net income to equity
SD	Standard deviation
S_i	market value of unlevered equity
Sm_i	sum of the total market value of unlevered equity
TBM	Two-Beta model
TS	Tax shields
UF	Unlisted firm
VAR	Vector autoregression
Var	Variance
V_L	Firm value
VTS	Present value of tax shields
V_U	Firm value based on non-debt Financing
WACC	Weighted average cost of capital
βl	Proxy levered Beta
β_m	Sharpe-Lintner CAPM beta
βu	Unlevered beta
Δ	Variation
λ (Paper 1)	Implied risk premium
λ (Paper 2)	Discrepancy term
τ	Corporate taxes

STATEMENT FROM CANDIDATE

This work has been conducted to meet the requirements of the PhD program at Macquarie University. This study has not been previously submitted to any other institution or University to attain a degree. Any material that belongs to other individuals or institutions has been acknowledged in the text. A reference list containing the material cited is also provided.

Julio Sarmiento-Sabogal
Student code:

To my beloved wife, Marcela, who left everything behind to join me in this adventure.

ACKNOWLEDGEMENTS

"With my whole being I sing endless praise to you. O LORD my God forever will I give you thanks" Psalms 30:13

I would like to begin by expressing my gratitude to Colciencias, Pontificia Universidad Javeriana, Macquarie University and LASPAU for giving me the opportunity to undertake my PhD studies.

I would like to express my gratitude to several contributors; without their inputs, this dissertation would have remained incomplete. I would like to thank my principal supervisor Dr. Mehdi Sadeghi for the countless hours expended reading, re-reading, criticizing, and correcting this dissertation. I would also like to thank my associate supervisor Ignacio Velez-Pareja for his support even prior to the commencement of this study.

I acknowledge the valuable feedback given by my colleagues Edgardo Cayon, Abdulnasser Hatemi-J, Hernando Diaz, and Terry Walter as well as the technical support provided by Juan Camilo Zapata and Carlos Pinzon.

I want to thank my fellow graduate students. Matias Vaira for his econometric assistance and Frances Chang for her comments. I am also thankful to Ade, Edward, Hector, Stanley, YunPing, Tandy, and all the PhD students in the faculty who have always provided a warm and productive learning environment. I would like to acknowledge the splendid job of the FBE-HDR office: Jee, Agnieszka, Eddy and Kaleen.

Finally, and most importantly, I would like to thank my family, particularly my wife Marcela who has supported me with patience and love during this journey. I would like to thank my parents, who are the two columns where I can ever rest and my daughter Valentina, the engine of my life.

ABSTRACT

This dissertation comprises three empirical papers that examine various methods of estimating the systematic risk of unlisted firms in order to identify more efficient ways of calculating their cost of equity capital.

Paper 1: *'The application of proxy methods for computing the cost of private equity: evidence from listed firms'.*

The two–beta model decomposes the systematic risk in the sensibility of cash flow and discount rate change. We propose a modified version of this model (MTBM) to compute the cost of capital for private equities (PEs). This model includes not only the accounting return reaction to long-term changes in consumption, but also links fundamental reactions to temporal changes in risk aversion. We test this model along with three traditional alternatives that are potentially useful in computing the cost of capital for PEs: accounting betas (BACC), unlevered betas (PLB), and operational betas (BOP). Using a two different tests, we gauge their capacity to explain cross-sectional stock returns and their forecasting abilities. We find that PLB, BACC, and MTBM are able to explain (with some limitations) the cross-sectional variations of stock returns. The forecasting experiment indicates that the MTBM produces the best output.

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Paper 2: '*Unlevered betas and the cost of equity capital: an empirical approach'.*

This paper calculates systematic risk based on the capital asset pricing model (CAPM) in order to determine the significance of financial leverage. Instead of testing the unlevered beta directly, we develop a multinomial model with theoretical targets in the unleveraged/leveraged process. We find that it is statistically more robust to include tax shields as a part of the unleveraged/leveraged process than to omit them. Our results also suggest that the use of the proxy levered beta to address the lack of market information for both non-traded firms and individual business units is not misleading.

Paper 3: *'Estimating the cost of equity capital for private firms using accounting fundamentals'.*

Financial literature suggests the use of BACC as a proxy for CAPM market beta (BMKT) when estimating the cost of equity capital in the absence of stock prices. Previous researchers have made this estimation by determining the correlation between

the accounting variables and BMKT. However, the magnitude of the resulting correlation error remains unknown. This study attempts to test the accuracy of BACC as a proxy measure for market risk and to examine the magnitude of error in correlation between these two measures. Our findings indicate that BACC over-estimates the BMKT by 20%–50%. This error may narrow to 22%–25% by applying corrective measures such as scaling operational earnings by equity; however, the error is not eliminated. Our output also suggests that BACC may be biased when assessing the risk of small firms.

This study concludes that MTBM seems to be a more efficient method for computing the cost of equity capital for unlisted firms than traditional methods. The results suggest that BACC and PLB, while less efficient, can still explain the behaviour of stock returns, albeit with limitations. In addition, these two methods are strongly related to market beta. However, both may exacerbate CAPM issues when computing the cost of equity capital for small firms.

INTRODUCTION

In business finance, sound cost of capital estimation is pivotal to a variety of investment decisions, from capital budgeting to project evaluation and mergers and acquisitions. This metric helps financial managers achieve their ultimate goal of maximising firm value and shareholders' wealth[1]. Consequently, financial literature suggests weighted average cost of capital (WACC) as the appropriate rate for discounting firms' expected future cash flows (Koller *et al.*, 2010; Kruschwitz and Löffler, 2006; Tham and Vélez-Pareja, 2004); WACC is determined according to the optimal capital structure (debt to equity ratio) as the value driver (since Modigliani-Miller (1958) seminal work). While it is relatively easy to estimate the cost of debt, it is not easy to accurately determine the cost of equity capital (Ke). Estimating the implied risk profile of stockholders' investments makes this computation difficult. Ke can be defined as the minimum rate of return required by shareholders in any given period.

Financial literature proposes two main approaches to calculate Ke. The first method is based on assessing the risk of the company using an asset pricing model and then estimating the required rate of return. The second method is based on the dividend valuation model and computation of the implied internal rate of return (IRR). However, both the approaches consider market price as a reasonable estimate of the true value of the company.

The need for publicly available data largely limits the application of these approaches to traded firms[2]. However, unlisted firms[3] (UFs) are important not only because of their large numbers, but also for their significant contribution to the gross domestic product (GDP). For instance, in the USA, around 99% of the registered companies are UFs[4] and their output accounts for around 50% of the GDP (Hope *et al.*, 2013). Moreover, mergers and acquisitions are as prevalent among UFs as public firms

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[1] See for example Andrew (2007), Damodaran (2010), Ehrhardt and Brigham (2009), Krishnamurti and Vishwanath (2009), Parrino and Kidwell (2009), Pettit (2007) and Ross *et al.* (2012) among others.

[2] Public companies are those whose shares are traded on the stock exchange. In this document, we use the terms public, listed, and traded companies interchangeably.

[3] Non-traded firms are those that are not listed on the stock exchange. We refer to them as private companies, non-traded firms, or unlisted firms.

[4] It is important to highlight that the low percentage of listed firms does not imply that they are irrelevant for the economy. This fact is confirmed by the percentage of market capitalization to GDP, which represents a large portion of the national economy in both developed and developing countries.

(Officer, 2007). The average annual growth rate of private equity investments in the USA during 1991–2012 has been around 15%, roughly double the growth rate of market capitalization of listed firms[5] (their market capitalization expanded from $8 billion in 1991 to over $148 billion in the last quarter of 2012). We expect that the importance of UFs in the USA and the rest of the world will continue to grow in the future.

The absence of market capitalization data to estimate UFs true value creates issues that affect the computation of Ke. In addition, it is unlikely that UFs will be covered by forecasting datasets such as I/B/E/S and Bloomberg[6]; hence, it is difficult to obtain a consensus on their future expected cash flows. Thus, previous studies have largely used data for publicly listed firms as a proxy for UFs in their empirical investigations. This study is not an exception either, as we were constrained to use the prevailing methodology in existing literature. This methodology also helped to overcome the lack of quality in the UFs[7] financial data. However, it has its own limitations, as we have to ignore the liquidity premium (Officer, 2007), size effect (Van Dijk, 2011), and other possible unique costs of UFs in our study.

The body of knowledge developed on asset pricing models over the past few decades for estimating Ke for listed firms is pretty impressive (Subrahmanyam, 2010). On the contrary, only a handful of studies have focused on calculating the cost of capital for UFs. Existing literature proposes three main solutions for estimating the risk profile of PE firms in order to determine their cost of capital.

i) Systematic risk decomposition in two components: financial leverage risk and the firm's intrinsic risk as measured by its unlevered beta. This method is proposed by Hamada (1972).

ii) Simply switching market return for an accounting measure of profit, called BACC, as proposed by Beaver *et al.* (1970).

[5] The average annual growth rate is from Private Equity Growth Capital Council (2013). The annual market capitalization is extracted from World Bank (2013).

[6] Financial information services firms like Bloomberg and I/B/E/S provide central tendency measures as "consensus forecasts" that are based on institutional investors' opinions.

[7] For example, Beuselinck and Manigart (2007), Burgstahler *et al.* (2006), Hope *et al.* (2013), and Katz (2009).

iii) The beta decomposition model that uses operational information from the income statement (BOP), as applied by Mandelker and Rhee (1984).

The notion behind PLB is that the systematic risk of the firm can be decomposed into financial leverage risk and the firm's intrinsic risk. Thus, the Sharpe-Lintner CAPM Beta (BMKT) is reduced to the latter by applying the firm's specific leverage ratio in order to obtain the unlevered beta. Hamada (1972) argues that the unlevered betas of firms in the same risk class should be equal. Many practitioners have exploited this idea for computing Ke. They first obtain the average unlevered beta of listed firms in the same risk class as that of the UF and then recalculate a proxy levered beta[8] based on the UF's leverage. However, this method has some limitations. First, there is little research on the empirical validity of this process[9]. Second, the role of debt tax shields (TS) in the decomposition is unclear. Academics have extensively discussed multiple contradictory models for this decomposition with little agreement. For instance, while Fernandez (2004, 2005, 2007) and Massari et al. (2008) argue that TS must be included in the unlevered beta formula, Arzac and Glosten (2005), Cooper and Nyborg (2006), Fieten *et al.* (2005), and Tham and Vélez-Pareja (2004) argue that TS must be excluded from this computation.

Another potential solution for computing the Ke of UFs is BACC. This method proposes a regression between a measure of accounting return and an index of changes in the market-wide excess-return in order to obtain an estimate of systematic risk (Beaver *et al.*, 1970). BACC was tested in the 1970s by determining its statistical relationship with BMKT. These early studies provided a general, although not unanimous, conclusion that BACC is significantly correlated with BMKT. Nevertheless, most recent studies provide contrary evidence to these findings. For example, Cohen *et al.* (2009) and Nekrasov and Shroff (2009) successfully apply BACC as a substitute for BMKT, while Campbell *et al.* (2010) find that BACC is a weak predictor of BMKT. In addition, the literature provides a number of accounting measures of return, while paying little attention to which of these metrics is empirically superior (if such superiority actually exists).

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[8] Note that the abbreviation PLB is derived from this unleveraging/re-leveraging process for determining the proxy levered beta.

[9] Bowman and Graves (2004), Bowman *et al.* (2005), and Bowman and Bush (2006) have conducted exploratory studies in Australia and US using a small sample of firms.

Although fewer studies have examined BOP as compared to the other two proxies, it is still an appealing model as it combines concepts from both PLB and BACC. In the application of BOP approach, Mandelker & Rhee (1984) follow the same underlying assumption of Hamada (1972) and Rubinstein (1973) in the sense that leverage is a driver of systematic risk. However, they used information from the income statement rather than the balance sheet. This approach allows them to further decompose systematic risk into three components: the degree of operational leverage that is measured as the difference between net income and EBIT, the degree of financial leverage that is computed as sales minus EBIT, and BACC. The model has certain caveats regarding its empirical application. First, the decomposition procedure creates an endogeneity issue because of the simultaneity of the factors. This problem is resolved by using either simultaneous equation models or instrumental variables. Second, related literature uses logarithmic transformations to control for the exponential behaviour of factors, thus limiting the application of this method to firms with strictly positive returns.

While these three methods have been tested separately, it is surprising that few studies have attempted to compare their relative performance and the accuracy of their outputs. Further, the testing approach is focused on the relationship between these methods and BMKT. In contrast, common tests applied in the context of asset pricing, such as the assessment of model's capacity to explain cross-sectional variation of stock returns, has been ignored. As a consequence, there are three different alternatives available (all with some degree of empirical validity, but no indicative degree of superiority) to both academicians and practitioners for calculating the Ke of UFs.

This dissertation attempts to address this research gap and examine new ways of computing Ke for UFs based on the most recent developments in asset pricing models. Specifically, the main objective of our study is to find more efficient methods for computing the Ke for UFs. Perhaps, a good way to highlight the importance of our aim is quoting some lines from Cochrane presidential address at the AFA annual meeting in 2011: "ASSET PRICES *SHOULD EQUAL expected discounted cash flows. Forty years ago, Eugene Fama (1970) argued that the expected part, "testing market efficiency," provided the framework for organizing asset-pricing research in that era. I argue that the "discounted" part better organizes our research today"* (p. 1047). We hope that our study offers some solutions to the problems faced by practitioners in computing the discount rate for UFs. This, however, comes at the cost of accepting some measurement errors in the estimation of discount rates using the existing asset pricing models. Fama and French (1997) find the two leading asset pricing models (CAPM and the three factor model[10]) to be "*unavoidably imprecise*" (p. 153) while Simin (2008) asserts that both models have *"little normative content"* (p. 372). Nonetheless, current literature suggests that the limitations of these asset pricing models do not invalidate their applicability to Ke computations (Da *et al.*, 2012).

This study comprises three empirical papers that address various issues raised above. The first paper titled '*The application of proxy methods for computing the cost of private equity: evidence from listed firms*' proposes a modified version of Campbell and Vuolteenaho (2004) two-beta model (TBM)[11] to estimate Ke for UFs, while at the same time it assesses the empirical validity of the other methods (PLB, BACC and BOP). The paper proposes a modified version of the TBM (MTBM) for computing Ke for UFs and then tests the developed method as well as PLB, BACC, and BOP, using a standard two-pass cross-sectional test for asset pricing models. The findings suggest that while PLB, BACC, and MTBM are able to explain, albeit with some limitations, the cross-sectional variation of stock returns, the empirical performance of BOP is poor. In addition, this study detects some limitations in the application of PLB and BACC to small firms. While the former is sensitive to the size of the firm[12], the latter suffers from estimates that may be indicative of a negative spurious correlation between BACC and BMKT. Through an extended forecasting test, we found that MTBM outperforms the other methods.

The second paper titled '*Unlevered betas and the cost of equity capital: an empirical approach*' focuses on two issues related to PLB: i) the theoretical discussion on which of the proposed models to compute unlevered beta has the best empirical performance, and ii) examining the validity of practitioners' unleveraged/re-leveraged method for estimating this variable. The paper derives an analytical model with two theoretically

[10] Graham and Harvey (2001) and Richardson *et al.* (2010) indicate that both academics and practitioners have a preference for these two methods.

[11] The two-beta model, also called "good beta and bad beta", is suggested by Campbell and Vuolteenaho (2004). They argue that there are two components of the market risk of a portfolio: shocks to cash flows (bad beta) and shocks to discount rates (good beta).

[12] This limitation was documented by Bowman and Bush (2006).

predicted components: the proxy levered beta (PLB) and the discrepancy term (λ). It is expected that the PLB will equal the BMKT, while λ will approach unity. This study finds that it is statistically more robust to include TS in the PLB calculation than to omit them. Although we are aware that an empirical test cannot resolve a theoretical debate, this study adds a novel dimension to this argument. The findings also suggest that it is not misleading to use PLB for computing Ke for UFs.

The third paper titled '*Estimating the cost of equity capital for private firms using accounting fundamentals*' addresses the BACC–BMKT relationship in four steps. First, we compute BMKT and eight versions of BACC using different time windows. Second, we run univariate longitudinal regressions between BMKT and each version of the BACC in order to determine whether all BACC estimates are statistically linked with BMKT. Third, we find possible explanations for the large group of negative BACC coefficients that are detected in the first step. Last, we measure the statistical significance of the difference between BMKT and its accounting counterparts. The results indicate that while BACC is strongly correlated with BMKT, its applicability to computing the discount rate for small firms leads to spurious, negative BACC coefficients. This study also finds that BACC over-estimates the BMKT by 20%–50%. This error is reduced to 22%–25% by using ratios such as *EBITDA* to Equity or *EBIT* to Equity.

The empirical procedure used in this dissertation comprises two approaches. In the first paper, we test whether proxy estimates are able to explain the cross-section of returns. Therefore, the well-known two-pass cross-sectional asset pricing model test is applied, where the factor loadings (betas) are estimated in the first step using the time-series dimension of the panel. The implied risk premiums (alphas) are obtained in the second pass by running a cross-sectional regression using estimates from the first step and the sample average stock returns. This method is commonly used in financial literature for testing asset pricing models. However, there is little research on its applicability for assessing the empirical validity of PLB, BACC, and BOP.

Papers 2 and 3 share the same methodological approach, which is different from the first paper. As all proxy methods have their theoretical foundation in the CAPM, researchers have commonly tested their relationship with BMKT. We use the same approach since testing PLB and BACC against BMKT helps in making theoretical predictions about the expected behaviour of empirical models. This methodology also allows us to examine the consistency of our results with previous literature. We make the implicit assumption that it is correct to use the CAPM model to calculate Ke[13]. This approach may be criticized given that the CAPM has failed to explain the behaviour of stock returns (Fama and French, 1996, 1997, 2004). However, the theoretical developments indicated by Stein (1996) and the new empirical findings of Cohen *et al.* (2009) support this assumption. Unlike previous studies, these two papers use a longitudinal approach that controls for *individual heterogeneity* (Baltagi, 2005).Thus, it captures the changes over time as well as differences among the firms.

The empirical tests are conducted at two levels of asset aggregation. The first paper uses portfolios ranked by book to market ratio. In the second and third papers, PLB and BACC are tested using stock-level data. The decision to conduct regressions at firm level rather than at portfolio level allows us to derive conclusions that are more useful for practitioners, although this adds noise to the results.

Overall, this dissertation suggests that MTBM is the most suitable method for computing KE for UFs. This output is in line with the call from Cochrane (2011), who concludes: *"Discount rates vary a lot more than we thought. Most of the puzzles and anomalies that we face amount to discount-rate variation we do not understand. Our theoretical controversies are about how discount rates are formed. We need to recognize and incorporate discount-rate variation in applied procedures."* (p. 1091). MTBM recognizes the asset sensibility to discount-rate variation by including a proxy of the "good beta"[14] estimate to the Ke computation. The MTBM updates the available methods for computing Ke for UFs firms that have been largely overlooked by academic research. However, the results also indicate that the common procedures used by practitioners are not misleading. In fact, both PLB and BACC are fairly indicative when tested at individual and portfolio levels.

[13] Note that this assumption is relaxed in the first paper.

[14] Campbell and Vuolteenaho (2004) termed asset sensibility to changes in discount rates as "good beta".

PAPER 1.

Presented at II Macao International Symposium on Accounting and Finance 2013, Macao SAR, November 2013.

The application of proxy methods for computing the cost of private equity: evidence from listed firms[1]

1.1 Introduction

The substantial growth of private equity investment in recent years has reinvigorated new business opportunities and entrepreneurial activities worldwide. According to the Preqin's[2] report, private equity funds have raised $311 billion during the first three quarters of 2013. This figure reflects a handsome growth of 20% relative to the $259 billion of capital raised in the first three quarters of 2012. Moreover, merger and acquisition activities by private firms have also been as prevalent, as in the case of public firms (Officer, 2007).

Despite the increasing importance of private equities (PEs), research in finance field has largely concentrated on public firms. For example, this shortcoming has prevailed in the computation of the hurdle rate needed to calculate the cost of private equity capital[3]. The most widely used models to estimate the cost of equity capital by both practitioners and academics, are the Capital Asset Pricing Model and the Three Factor Model (see for example Graham and Harvey (2001)). However, the market variables required for their calculation imposes limits on their application to private firms.

Financial economists have proposed resolutions to this issue, either by the application of accounting fundamentals as a substitute for unknown market variables in the asset pricing models or the use of information from comparable listed companies as proxies for these variables. In fact, three of the most common solutions to this problem are based on CAPM: The first method involves the simple switching from the market beta model to the accounting beta (BACC) model (Beaver *et al.*, 1970). The second method is based on beta decomposition by leverage, commonly known as unlevered

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[1] Sarmiento-Sabogal, Julio and Sadeghi, Mehdi. Candidate contribution: data collection, literature review, research design and analysis of results, which account for about 90% of the paper. The co-author have contributed with his comments and corrections of the paper.

[2] https://www.preqin.com

[3] The hurdle rate for equity represents the minimum rate of return that a firm must generate on its equity to satisfy its investors. It is practically equal to the cost of equity capital for the firm.

betas (PLB hereafter[4]) (Hamada, 1972), and the third approach relies on beta decomposition by operational information from an income statement, so-called operational betas (BOP).

These three methods have been tested separately by previous researchers (see for example Chung (1989), and Cohen *et al.* (2009)). However, there is little information regarding which of these approaches is more accurate and whether they are interconnected. Consequently, those who deal with the cost of PE may choose any method, without exactly knowing which one actually performs better. By testing the empirical ability of these methods to explain the behaviour of stock returns, this study attempts to fill this research gap.

We also propose a modified version of the two beta decomposition model (MTBM), suggested by Campbell and Vuolteenaho (2004) and extended by Campbell *et al.* (2010), that does not require market information in its computation. MTBM links the accounting return at asset level with shocks in temporal risk aversion at market level, improving the assessment of an asset's risk profile. In other words, we explore the idea that the PEs risk profile is given by its aggregated sensibility to changes in cash flows and discount news at market level. The former is estimated as the reaction of the individual company's accounting return to changes at the aggregated level and the latter as the covariance between the individual accounting return and a selected proxy of market-level changes in discount rates. We test this model against other traditional methods in the context of traded firms, in order to avoid the lack of financial reporting for unlisted firms (Beuselinck and Manigart (2007), Burgstahler *et al.* (2006), Hope *et al.* (2013) and Katz (2009)). However, this methodology comes at a cost, since it does not allow us to control for illiquidity premiums (Officer, 2007), size effect (Van Dijk, 2011), and other possible factors that are unique in estimating the costs of PE capital.

This paper tests the four competing models in two steps. First, we use the standard test, computing the implied risk premium of the computed estimates. Second, we check the empirical ability of each model to forecast future returns. We accomplish this

[4] Note that unlevered beta should be re-levered to be useful for Ke estimation. Therefore, we call this result a proxy levered beta (PLB).

purpose by estimating the outputs of the four competing models with information from US listed firms[5].

Our results suggest that PLB, BACC, and MTBM explain the cross-section of stock returns, with some limitations. However, we do not find a significant relationship between BOP and stock returns. The forecasting experiment indicates that although PLB, BACC, and *TBM* have some forecasting power, MTBM seems to produce smaller estimation errors.

This paper contributes to the literature by providing a new approach to compute the cost of capital for PEs. MTBM incorporates information regarding the fundamental portfolio-level reaction to the shocks in discount rates (or business cycles), filling the gap between accounting information and short-run innovations in a very efficient way. Unlike previous studies, we compare the empirical ability of proxy methods to explain the cross-section of stock returns as well as their forecasting performance. Our findings should be able to help practitioners who commonly use proxy methods without exactly knowing which model offers a better empirical performance.

The remainder of this paper is structured as follows. Section 2 presents MTBM. Section 3 explains its detailed dataset and methodology. Section 4 reports the dataset and the empirical results. Section 5 concludes.

1.2 Two-Beta model, PE, and MTBM

According to Campbell and Vuolteenaho (2004), market portfolio returns are driven by two components: shocks affecting long-term wealth or changes in cash flows (CF) and shocks changing investor temporal risk aversion or variations in discount rates (DR). They call CF ‘bad beta’ because it captures long run risk (i.e. changes in future wealth or production) that is related to a firm’s fundamentals (cash flows). They term DR ‘good beta’, since the asset return reaction to DR describes temporal changes in risk aversion that are easily avoided by a buy-and-hold strategy. Formally, the annual expected stock return $\left(r_{t+1} - E(r_{t+1)}\right)$ is an approximate loglinear function of changes

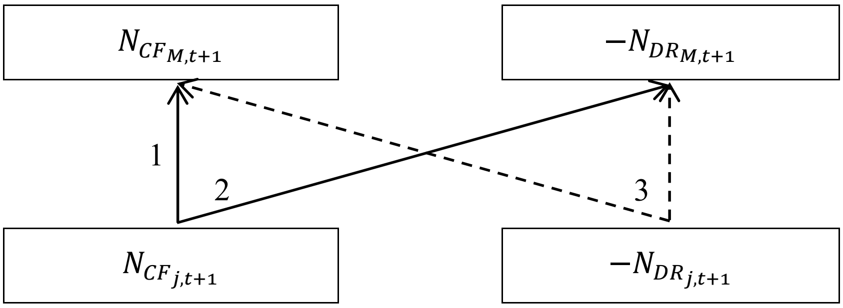
[5] Note that PE does not have a market value as a target for comparison; therefore, measuring the accuracy of the competing methods in the stock market and extrapolating the results to PE seems to be a plausible solution.

or news (*N*) regarding CF and DR. While an increase in the first component implies a shift in the return, an increment in the latter indicates a drop in the same measure. Thus,

$$r_{t+1} - E_t(r_{t+1}) = N_{CF_M,t+1} - N_{DR_M,t+1} \tag{1.1}$$

where r represents return and E(.) is the expectation operator. Reproducing equation (1.1) at asset level, Campbell *et al.* (2010) propose a four beta model that allows cross-correlations among asset-level *CF* betas and *DR* shocks and *DR* betas with *CF* shocks. A simple graphical explanation helps us to illustrate this situation:

Figure 1. Four-beta decomposition model in PE context



The upper row of Figure 1 represents the market-level decomposition suggested by Campbell and Vuolteenaho (2004) (TBM hereafter), while the lower row characterizes the asset level decomposition implemented by Campbell and Mei (1993b). Continuous lines (1, 2) show the link of the asset-level cash flow betas with CF and DR shocks. Dashed lines (3, 4) present the association of asset-level discount rates with CF and DR shocks. This framework is convenient for PEs, since it permits us to extract (at least in part) information on whether asset fundamentals are related to short-term fluctuations (DR). However, we are not able to compute the full model for PEs because we require the market price at firm level, which is missing. However, we are still able to use relations 1 and 2 and assume that relationships 3 and 4 are zero.

Formally, following Campbell *et al.* (2010), we combine the market-level and portfolio-level decomposition and obtain an structure of four beta components[6]:

[6] Note that the model is set to allow an *ex-post* analysis since future shocks are not observable. This change implies the usual bias of *ex-post* models (Brown and Walter, 2013)

$$\beta_{CFj}^{CFM} \equiv \frac{Cov\left(N_{CF_j}, N_{CF_M}\right)}{Var\left(r_M\right)} \tag{1.2}$$

$$\beta_{DRj}^{CFM} \equiv \frac{Cov\left(-N_{DR_j}, N_{CF_M}\right)}{Var\left(r_M\right)} \tag{1.3}$$

$$\beta_{CFj}^{DRM} \equiv \frac{Cov\left(N_{CF_j}, -N_{DR_M}\right)}{Var\left(r_M\right)} \tag{1.4}$$

$$\beta_{DRj}^{DRM} \equiv \frac{Cov\left(-N_{DR_j}, -N_{DR_M}\right)}{Var\left(r_M\right)} \tag{1.5}$$

We assume $\beta_{DRj}^{DRM} + \beta_{DRj}^{DRM} = 0$ as a correct error in this relationship, since the individual asset short-term fluctuations $\left(-N_{DR_j}\right)$ are missing in the PE context. We normalize the covariance estimates in equations (1.2) and (1.4), scaling by the variance of N_{CF_j} and $-N_{DR_j}$, respectively[7]. In sum, our model captures the fundamental reaction to innovations in CF and DR.

1.3 Data and Methodology

1.3.1 Dataset

The dataset is composed of 58,607 firm-year observations of NYSE, AMEX, and NASDAQ listed firms from 1970 to 2011. Accounting information is retrieved from COMPUSTAT, and the market information is obtained from the Centre of Research of Security Prices' (CRSP) annual security file. We exclude firms with fiscal years that end other than in December and firms whose market information is less than 36 consecutive months. We require the firm-year observation to have existing values for NI, BE, EBIT, EBITDA, debt, market capitalization, and equity. We also require that companies have two years of available information in CRSP to diminish the survivorship bias. We discard firms with debt to book value of equity higher than 10 because they are (or are towards to) bankrupt (Marston and Perry, 1996).

[7] Campbell and Vuolteenaho (2004) employ $\widehat{Var}\left(\hat{N}_{CF,t} - \hat{N}_{DR,t}\right)$ to normalize the covariance estimates. We use a parsimonious version of this approach.

Panel A of Table 1-1 shows the summary statistics of the selected variables before the portfolio construction. Income statement[8] variables are highly positively skewed. For example, the average sales and net income exceed 9 and 12 times the median, respectively. The annual stock return is 18%, while the median is 15%. These coefficients are statistically higher than those reported by Cohen *et al.* (2009)[9]. Since their dataset covers the years 1928-2000, our finding may indicate that stock returns have been increasing and diverging from a normal shape over time. BOP related literature has usually employed a relatively small dataset for non-financial firms in S&P 500 index. It also imposes a strictly positive EBIT and NI requirement. We mimic this specification in our dataset (Table 1-6), and the number of firm-year observations decreases from 58,607 to 8,265. Although the mean and median values seem to remain relatively stable, the standard deviation drops by about half of our complete sample.

Panel B of Table 1-1 presents the summary statistics of the estimated variables. The means of BMKT (denoted by β_j^{MKT}) (0.97) and PLB (1.04) are towards (but not equal to[10]) the unity. In contrast, the estimated coefficient (0.38) of BACC (denoted by β_j^{ACC}) seems to be smaller than the expected value of unity. We find in Paper 3 that this downward bias may come from a group of spurious negative β_j^{ACC} estimates that are associated with small firms. The output also suggests that this issue may be alleviated by adopting the long-term aggregation suggested by Cohen et al. (2009), since bad beta (denoted by β_{CFj}^{CFM}) reports estimates closer to one; the only difference between them is this aggregation; however, we use annual returns, and they compute prices for a ten years period. The volatility also may decrease when the long-term aggregation is adopted.

1.3.2 Methodology

We estimate the outputs of the four competing models: MTBM, PLB, BACC, and BOP over 20 value-weighted portfolios of book to market ratios (*B/E*) at the end of

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[8] Income Statement information in thousands.

[9] The null hypothesis that the mean of our sample is equal to 15.5% was rejected for the *t-test*, and the Wilcoxon signed rank test rejected the null hypothesis that the median is equal to 5.4%.

[10] The *t-test* indicates that *BMKT* and *PLB* are significantly different from 1. The outputs of the Shapiro–Wilk normality test are presented in Table 1-7.

April of each year. *B/E* is calculated using the market equity of April[11] and the book value of equity for the lagged fiscal year. We require the firm to have *B/E* between 0.01 and 100 in order to limit the effect of outliers Cohen *et al.* (2003).

<u>*Modified two-beta decomposition model (MTBM)*</u>

Equation (1.1) implies that unexpected stock returns should decompose into CF and DR. Nevertheless, the appropriate decomposition method remains unclear. Campbell and Vuolteenaho (2004) follow Campbell (1991) VAR approach to directly measure the DR shocks and compute CF as a residual, backing out the difference between the unexpected returns and discount-rate news. This method is criticized by Chen and Zhao (2009), who argue that the model is sensitive to the VAR specification; thus, other reasonable VAR specifications lead to different results. In turn, Engsted *et al.* (2012) criticize the conclusions of Chen and Zhao (2009) and assert that the VAR model would be applicable under certain conditions, such as the inclusion of a measure of P/E ratio and interest rate news in the set of state variables. Bianchi (2010) points out that the capacity of *TBM* to explain stock returns depends on the sample selection and that statistical performance relies on the inclusion of data from the Great Depression of the thirties, since the TBM poorly performs when this crisis is excluded from the sample.

There are a number of alternative strategies for this decomposition. For example, Ball *et al.* (2009) use principal component analysis to extract separately the systematic component of both CF and DR. Campbell *et al.* (2010) directly measure CF and DR by using proxies for both of them. Wang *et al.* (2012) employ an state-space decomposition and find that this method better explains cross-sectional variations of stocks than the proxy model of Campbell *et al.* (2010).

We follow the direct calculation of CF and DR by Campbell *et al.* (2010) because this setting can be straightforwardly applied to PEs, as it only requires accounting information at firm level. At the same time, this approach eliminates the selection of the state-variable problem. The market-wide *ROE* is computed as a proxy for CF: $N_{CF_M,t} = \sum_{k=0}^{K} \rho^{k-1} ROE_{M,t-k}$, where K is the time horizon that removes the short-term fluctuations set to 5. Subscript M denotes the aggregate market return. The market

[11] Note that most annual financial statements are released from February to March. Therefore, April market prices should reflect the new accounting information.

aggregation is based on a value-weighted portfolio composed of all firms in the sample. ρ *is* the discount factor set as[12] 1/0.95. *ROE* is explained in equation (1.7). The negative *DR* shocks are proxied by the lagged difference (Δ) of the *P/E* ratio at market level: $-N_{DR_M,t-1} = \sum_{k=1}^{K}\left[\rho^{k-1}\Delta_{t-k}\ln(P/E)_M\right]$, where $\Delta_{t-k}\ln(P/E)_M$ represents the lagged difference of the *P/E* ratio at market level[13].

*Proxy levered betas (*PLB*)*

We calculate the unlevered beta $\left(\hat{b}^u\right)$ for each firm (i) in the sample by using the Rubinstein (1973) definition: $\hat{b}_i^u = \hat{\beta}_i^{MKT}/\left[1+\left(\overline{BD_i}/\overline{BE_i}\right)(1-\bar{\tau})\right]$, where *BD* is the book value of debt[14], *E* is the market value of equity, and τ is the corporate tax rate[15] and the overbar represents the time series sample averages. The CAPM beta $\left(\hat{\beta}_i^{MKT}\right)$ is estimated at firm level before the portfolio formation. We treat negative $\hat{b}^u$ estimates as missing values.

$\hat{\beta}_i^{MKT}$ is computed in the standard form $\hat{\beta}_i^{MKT} = Cov(r_i, r_M)/Var(r_M)$, where r_i is the excess return of the firm. The excess return is computed as the difference between the portfolio monthly return and the 30-day Treasury bill rate. r_M is the monthly sample value-weighted portfolio return.

We mimic a commonly used procedure to compute the β_i^{PL} for PEs by applying the company's average leverage ratio $(\overline{BD_i}/\overline{BE_i})$ to the out-of-sample mean of the firm's risk class $\left(\bar{b}_y^u\right)$. Note that we use book values to replace the absent market values in PEs context. Thus,

$$\beta_i^{PL} = \bar{b}_y^u\left[1+\left(\overline{BD_i}/\overline{BE_i}\right)\left(1-\bar{\tau}\right)\right] \tag{1.6}$$

[12] For Campbell *et al.* (2010), K = 5 and ρ=0.95. Our *ex-post* model implies the inverse of ρ because we are computing future values rather than present values.

[13] P/E ratio has been made available by Professor Shiller at his web page http://www.econ.yale.edu/~shiller/data.htm.

[14] Although the formal definition of b^u uses the market value of debt rather than its book value, previous studies have shown that this is not likely to affect our results (Bowman, 1980; Mulford, 1985).

[15] The discussion regarding the theoretical implications of including taxes in the unlevered betas is still unresolved. However, In Paper 2 we argue that models including this factor outperform those that omit it.

The risk class (y) is defined by the industrial classification and the size of the firm. The former is taken from Fama–French 12 industry specification[16], and the latter is defined as the quintile sorted by market capitalization. β_i^{PL} is computed at firm level and aggregated at portfolio level. The out-of-sample yearly mean of each class is $\bar{b}_y^u = [1/(N-1)]\sum_{y=1}^{N} b_y^u - b_i^u$, where i is a firm in the y^{th} risk class[17]. Note that this setting avoids any possibility of circularity by removing the firm-specific observation from $\bar{b}_y^u$.

<u>*Accounting Betas (*BACC*)*</u>

In paper 3, we argue that although BACC tends to overestimate systematic risk when compared with the market model, measures based on *EBITDA* to book value of equity (*EBCE*) minimize this issue. This finding is in line with the common use of *ROE*[18] as a fundamental proxy of return, as well the conclusions of Barton *et al.* (2010), who assert that measures of the middle of income seem to be more relevant for investors than other performance metrics. Therefore, we define fundamental return as:

$$EBCE_{i,t} = \log\left(1 + \frac{EBITDA_{i,t}}{BE_{i,t-1}}\right) - \log\left(1 + R_f\right), \tag{1.7}$$

where R_f is the risk free rate. The logarithmic transformation of EBCE is taken from Vuolteenaho (2002); it helps us to smooth series that commonly have nonlinear behaviour. BACC is the estimated coefficient from a time-series regression between the portfolio *EBCE* and the value-weighted market portfolio composed by the firms in the sample. Thus,

$$\beta_j^{ACC} = \frac{Cov\left(EBCE_j, EBCE_M\right)}{Var\left(EBCE_M\right)} \tag{1.8}$$

<u>*Operational betas (BOP)*</u>

Mandelker & Rhee (1984) decompose the CAPM beta by isolating the Degree of Operating Leverage *(DOL)* and the Degree of Financial Leverage *(DFL)* from systematic risk. The authors make a further decomposition of Hamada (1972) and

[16] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[17] We require at least three observations for each risk class to compute $\bar{b}_y^u$.

[18] See, for example, Baginski and Wahlen (2003), Cohen *et al.* (2003), Nekrasov and Shroff (2009), Cohen *et al.* (2009), and Campbell *et al.* (2010), among others.

Rubinstein (1973) model, developing the system: $\hat{\beta}_j^{MKT} = (DOL_{j,t})(DFL_{j,t})(BACC_{j,t})$, where $DOL_{j,t} = \Delta_t EBIT_j / \Delta_t Q_j$, $DFL_{j,t} = \Delta_t NI_i / \Delta_t EBIT_j$ and the accounting beta is computed as[19]: $BACC_{j,t} = Cov\left((NI_{j,t-1}/EBIT_{j,t-1})(EBIT_{j,t}/E_{j,t-1}), r_{M,t}\right)/Var(r_{M,t})$, where *NI* is net income.

Some researches, such as Mensah (1992) and Griffin and Dugan (2003), include further decompositions of business risk. Schlueter and Sievers (2011) argue that growth risk (*GRWT*) is the only factor that improves the explanation of the systematic risk beyond *DOL* and *DFL*. We adopt the later approach and define the operational decomposition as:

$$\beta_j^{OP} = \left(DOL_j\right)\left(DFL_j\right)\left(GRWT_j * ROE_j\right) \tag{1.9}$$

Equation (1.9) provides a convenient framework for PEs, since the only required adjustment is the use of the book value of equity as a proxy for market value[20]. We implement this model, following Chung (1989), and compute a simultaneous equation model:

$$NI_{j,t} = \lambda_{j,t} + \lambda_{j,t} EBIT_{j,t} + u_{j,t} \tag{1.10}$$

$$EBIT_{j,t} = \phi_{j,t} + \phi_{j,t} S_{j,t} + v_{j,t} \tag{1.11}$$

$$S_{j,t}/S_{j,t-1} = \gamma_{j,t} + \gamma_{j,t}\left(S_{M,t}/S_{M,t-1}\right) + w_{j,t}\,, \tag{1.12}$$

where u, v, and w are error terms. Equation (1.12) represents *GRWT*. We then compute DFL and DOL by using the estimated coefficients from equations (1.10) and (1.11): $DFL = \hat{\lambda}_i(\overline{EBIT}_i/\overline{NI}_i)$ and $DOL = \hat{\phi}_{i,t}(\bar{S}_i/\overline{EBIT}_i)$.

[19] Note that *BACC* definition in *BOP* context is similar but not equal to the one we use in equation(1.8).

[20] Note that the complete setting of *BOP* assumes that accounting earnings are a good proxy of market return. For example, equation 5 of Mandelker and Rhee (1984) implicitly makes this assumption.

1.4 Empirical test and results

1.4.1 Estimating the implicit risk premium

We begin testing the models with a standard two-pass cross-sectional regression methodology. Although this method is standard in the literature, we briefly introduce its unconditional version to ease future discussion. Thus,

$$\overline{r_j} = \beta_j{}'\lambda_j, \tag{1.13}$$

where $\bar{r}_j$ is the sample average excess return of the portfolio: $\bar{r}_j = \bar{R}_j - r_f$. β' is a vector of k factor loadings, defined for each pricing model discussed in section 3 (i.e. k = 1 for PLB and BACC, k = 2 for MTBM and k = 4 for BOP). These betas are estimated running separate OLS regressions for each portfolio, using the time series dimension of the panel. In a second pass, the implied risk premiums (λ) are obtained with cross-sectional regressions. We expect $\lambda_0 = 0$ and all other alphas to be positive.

The implied risk premiums (λ) for BACC and PLB are, respectively, estimated as:

$$\bar{r}_j = \lambda_0^{PL} + \lambda_{PL}\hat{\beta}_j^{PL} + e_1 \tag{1.14}$$

and

$$\bar{r}_j = \lambda_0^{ACC} + \lambda_{ACC}\hat{\beta}_j^{ACC} + e_2. \tag{1.15}$$

$\hat{\beta}_j^{PL}$ is obtained from equation (1.6) and $\hat{\beta}_j^{ACC}$ is estimated from equation (1.8). The implied risk premiums for other methods are calculated in a similar way.

The cross sectional estimation of the MTBM is:

$$\bar{r}_j = \lambda_0^{MTBM} + \lambda_{CF}\hat{\beta}_j^{CF} + \lambda_{DR}\hat{\beta}_j^{DR} + e_3 \tag{1.16}$$

Campbell and Vuolteenaho (2004) argue that $\hat{y} = \lambda_{CF}/\lambda_{DR}$ is the risk aversion coefficient.

Finally, the BOP is fitted as:

$$\log\left(\bar{r}_j\right) = \lambda_0 + \lambda_{GRWT}\log\left(\widehat{GRWT}_j\right) + \lambda_{DFL}\log\left(\widehat{DFL}_j\right) + \lambda_{DOL}\log\left(\widehat{DOL}_j\right) + \lambda_{ROE}\log\left(\overline{ROE}_j\right) + e_4$$
(1.17)

The model specification of equation (1.17) employs a logarithmic transformation to control for the nonlinear behaviour of DOL and DFL reported in previous research[21].

Table 1–2 presents the implied risk premium of the studied models (fitted results of equations (1.14) to (1.17)). Each column presents the aggregated premium estimates for each model. The second row of each estimate reports the Standard error calculations according to the Huber–White sandwich estimators[22]. The implied risk premium for the BACC coefficient is 0.18, seemingly high when compared with output from Cohen *et al.* (2009), which is around 15%. The estimated coefficient for the PLB seems to be excessively high (69%) as an average risk premium. The estimated premium for N_{CF_M} is 0.45, while the same figure for $-N_{DR_M}$ is 0.10. These figures provide evidence that although stock returns react more strongly to CF news, they are also influenced by DR news. This finding is in line with Campbell *et al.* (2010) and confirms our initial caveat about the usefulness of linking the individual portfolio accounting return with temporal changes in consumption.

A further exploration of Table 1–2 suggests that all coefficients are significant at the conventional levels, with the exception of the BOP. The output of the *BOP* indicates that the *DOL, GRWT, and ROE* estimates are not significantly different from zero[23]. The BOP also eliminates the results of two out of twenty portfolios because of negative *NI* averages. This situation is exacerbated when we use 40 portfolios for the robustness check (Table 1-3). It seems like the BOP has a poor performance when used in a generalized context, with a dataset that included observations beyond the manufacturing sector.

Overall, confirms that BACC, PLB*,* and MTBM are able to explain the cross-section of returns. However, the testing of implied premia is problematic. For example, we are not looking at the time series properties of our estimates. This topic has been extensively researched (see for example Harvey (1989), Lettau and Ludvigson (2001)

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[21] See, for example, Mandelker and Rhee (1984), Chung (1989), and Schlueter and Sievers (2011), among others.

[22] The results seem to be not sensitive to the selection of the standard errors estimators. Table 1-8 presents the results running OLS regressions and the outputs of the Breusch–Pagan/Cook–Weisberg test for the homoscedasticity of the residuals. Table 1-9 reports the output of MacKinnon–White heteroskedasticity-consistent estimators in small samples.

[23] These findings hold when we use a different number of portfolios, as presented in Table 1-3.

and (Lewellen and Nagel, 2006) among others). Second, the constant term is both negative and significant, while the expectation is an estimate insignificantly different from zero (Black et al., 1972). Therefore, we further test whether these estimates are able to forecast future returns.

1.4.2 Measuring the forecasting ability of the studied methods

Although the measure of the implied risk premium is theoretically appealing, we contend that the true usefulness of these models rest with their capacity to forecast future returns. Therefore, we create a subsample composed of observations from the years 1970 to 2008 (reported in Table 1-4) and re-calculate all coefficients to forecast two and three years future returns. The expected output from each model is defined as $\hat{r}_j = \sum_{z=1}^{Z} \hat{\beta}_z\, (\hat{P}_z)$, where $\hat{r}_j$ is the estimated return of each model, subscript z represents the number of factors in the model, and $\hat{\beta}_z$ and $\hat{P}_z$ are the estimated coefficients taken from Table 1-4. The realized returns are the simple average from 2009 to 2011($\bar{r}_{09-11}$) and 2009 to 2010 ($\bar{r}_{09-10}$)[24].

We also apply a non-parametric ranking test to measure the forecasting errors, based on Nekrasov and Shroff (2009). The average errors $(\hat{E})$ are computed, first sorting the firms by $\hat{r}_j$ each year and then sorting them independently by the realized returns ($\bar{r}$). This test is less sensitive to outliers and large errors. Thus,

$$\hat{E}=1/\mathrm{T}\sum_{t=1}^{T}\mathrm{ABS}\left[(\varphi\left(\hat{r}_i\right)-\omega\left(\bar{r}_i\right)\right], \tag{1.18}$$

where φ represent the rank position in the expected return sorting, and ω is the ranking of the realized returns. Table 1-5 presents the outputs of the forecasting ability of the methods. We expect the coefficient to be approaching unity, since a smaller (larger) estimate implies an underestimation (overestimation) of the future return. The output of Panel A in Table 1-5 shows that all estimates tend to underestimate the future return (BACC = 0.83, PLB = 0.4, and MTBM = 0.93). In other words, they all tend to overestimate the cost of equity capital. This situation is exacerbated for shorter time intervals (Panel B), diluting the BACC estimate for its capacity to predict the rate of return within this time window. Comparing the estimates of the three models, MTBM

[24] Recent literature empathizes in the use of long-run returns. See for example Cohen *et al.* (2009) and Campbell *et al.* (2010).

result seems to be closer to the expectation. This conclusion is further supported by the non-parametric tests, as the ranking errors generated by MTBM are consistently smaller than those produced by other models.

1.5 Conclusions

The lack of market information on capital for private firms creates two unavoidable problems in estimating the cost of equity capital: First, there is no reasonably easy and quick way to estimate the true value of a company. Second, the reaction of the firm's fundamental measures (accounting) to changes in business cycle is not predictable (Jenkins *et al.*, 2009; Johnson, 1999). These issues exacerbate the already complex problem of further computing the cost of equity capital for firms if they go public.

We propose the use of modifying the two beta decomposition model (MTBM) suggested by Campbell and Vuolteenaho (2004) and extended by Campbell *et al.* (2010) to a four beta version in order to estimate the cost of equity capital for PEs. Our modified model includes not only the reaction of accounting fundamental variations to the long-term changes in consumption (CF news), but also links the cash flow reactions to temporal changes in risk aversion (or business cycle). Therefore, it captures (at least in part) the missing market information regarding the firms' reactions to short-term and long-term shocks.

Along with MTBM*,* we have tested three alternative options to compute the cost of equity capital for PEs: accounting betas (BACC), defined in Beaver *et al.* (1970) as the regression between a measure of accounting return and a market-wide index of earnings; unlevered betas (PLB), derived from Hamada (1972); and operational betas (BOP), suggested by Mandelker & Rhee (1984). These coefficients, which are estimated by using the time series dimension of the panel, are tested for their empirical capacities to explain the cross-section of the average stock returns. We extend our test, splitting the sample in two (unequal) parts in order to use the re-calculated estimates in the first segment to forecast the future (second segment) returns.

Our findings indicate that BACC*,* PLB*,* MTBM explain (with some limitations) stock returns. However, we failed to find a significant relationship between BOP and some cross-sectional measures of these returns. This finding contradicts the general consensus in the literature regarding the good empirical performance of BOP (see, for example, Mandelker and Rhee (1984) Chung (1989), Mensah (1992), Griffin and

Dugan (2003) and Schlueter and Sievers (2011) among others). We assert that the different findings may be attributed to difference in the datasets. While the BOP literature uses manufacturing firms with strictly positive earnings, we employ a more general sample, including firms from all economic sectors, with no restrictions on regarding earnings. The forecasting experiment results suggest that although BACC*,* PLB*,* and MTBM have some forecasting ability, all of them tend to underestimate future returns. Comparing the expected properties of the forecasting estimates, MTBM produces the best result.

1.6 References

Baginski, S. P., & Wahlen, J. M. 2003. Residual income risk, intrinsic values, and share prices. ***The Accounting Review***, 78(1): 327-351.

Ball, R., Sadka, G., & Sadka, R. 2009. Aggregate earnings and asset prices. ***Journal of Accounting Research***, 47(5): 1097-1133.

Barton, J., Hansen, T. B., & Pownall, G. 2010. Which performance measures do investors around the world value the most and why? ***The Accounting Review***, 85(3): 753-789.

Beaver, W., Kettler, P., & Scholes, M. 1970. The association between market determined and accounting determined risk measures. ***The Accounting Review***, 45(4): 654-682.

Beuselinck, C., & Manigart, S. 2007. Financial reporting quality in private equity backed companies: The impact of ownership concentration. ***Small Business Economics***, 29(3): 261-274.

Bianchi, F. 2010. Rare events, financial crises, and the cross-section of asset returns. ***Economics Research Initiatives at Duke (ERID) Working Paper***(41).

Black, F., Jensen, M., & Scholes, M. 1972. ***The capital asset pricing model: Some empirical tests***: Praeger Publishers.

Bowman, R. 1980. The importance of a market-value measurement of debt in assessing leverage. ***Journal of Accounting Research***, 18(1): 242-254.

Brown, P., & Walter, T. 2013. The CAPM: theoretical validity, empirical intractability and practical applications. ***Abacus***, 49(S1): 44-50.

Burgstahler, D. C., Hail, L., & Leuz, C. 2006. The importance of reporting incentives: earnings management in European private and public firms. ***The Accounting Review***, 81(5): 983-1016.

Campbell, J., Polk, C., & Vuolteenaho, T. 2010. Growth or glamour? fundamentals and systematic risk in stock returns. ***Review of Financial Studies***, 23(1): 305-344.

Campbell, J. Y. 1991. A variance decomposition for stock returns. ***Economic Journal***, 101(405): 157-179.

Campbell, J. Y., & Mei, J. 1993. Where do Betas Come From? Asset Price Dynamics and the Sources of Systematic Risk. ***The Review of Financial Studies***, 6(3): 567-592.

Campbell, J. Y., & Vuolteenaho, T. 2004. Bad beta, good beta. ***American Economic Review***, 94(5): 1249-1275.

Chen, L., & Zhao, X. L. 2009. Return decomposition. ***Review of Financial Studies***, 22(12): 5213-5249.

Chung, K. H. 1989. The impact of the demand volatility and leverages on the systematic risk of common stocks. ***Journal of Business Finance & Accounting***, 16(3): 343-360.

Cohen, R., Polk, C., & Vuolteenaho, T. 2003. The value spread. ***The Journal of Finance***, 58(2): 609-642.

Cohen, R., Polk, C., & Vuolteenaho, T. 2009. The price is (almost) right. ***Journal of Finance***, 64(6): 2739-2782.

Daniel, K., & Titman, S. 2006. Market reactions to Tangible and intangible information. ***The Journal of Finance***, 61(4): 1605-1643.

Engsted, T., Pedersen, T. Q., & Tanggaard, C. 2012. Pitfalls in VAR based return decompositions: A clarification. ***Journal of Banking & Finance***, 36(5): 1255-1265.

Graham, J. R., & Harvey, C. R. 2001. The theory and practice of corporate finance: evidence from the field. ***Journal of Financial Economics***, 60(2-3): 187-243.

Griffin, H. F., & Dugan, M. T. 2003. Systematic risk and revenue volatility. ***Journal of Financial Research***, 26(2): 179-189.

Hamada, R. S. 1972. The effect of the firm's capital structure on the systematic risk of common stocks. ***The Journal of Finance***, 27(2): 435-452.

Harvey, C. R. 1989. Time-varying conditional covariances in tests of asset pricing models. ***Journal of Financial Economics***, 24(2): 289-317.

Hope, O.-K., Thomas, W. B., & Vyas, D. 2013. Financial reporting quality of U.S. private and public firms. ***The Accounting Review***, 88(5): 1715-1742.

Jenkins, D. S., Kane, G. D., & Velury, U. 2009. Earnings Conservatism and Value Relevance Across the Business Cycle. ***Journal of Business Finance & Accounting***, 36(9-10): 1041-1058.

Johnson, M. 1999. Business cycles and the relation between security returns and earnings. ***Review of Accounting Studies***, 4(2): 93-117.

Katz, S. P. 2009. Earnings quality and ownership structure: The role of private equity sponsors. ***The Accounting Review***, 84(3): 623-658.

Kemsley, D., & Nissim, D. 2002. Valuation of the debt tax shield. ***Journal of Finance***, 57(5): 2045-2073.

Lettau, M., & Ludvigson, S. 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying

arying. ***Journal of Political Economy***, 109(6): 1238-1287.

Lewellen, J., & Nagel, S. 2006. The conditional CAPM does not explain asset-pricing anomalies. ***Journal of Financial Economics***, 82(2): 289-314.

Mandelker, G. N., & Rhee, S. G. 1984. The Impact of the degrees of operating and financial leverage on systematic risk of common stock. ***Journal of Financial & Quantitative Analysis***, 19(1): 45-57.

Marston, F., & Perry, S. 1996. Implied penalties for financial leverage: theory versus empirical evidence. ***Quarterly Journal of Business & Economics***, 35(2): 77-97.

Mensah, Y. 1992. Adjusted accounting beta, operating leverage and financial leverage as determinants of market beta: A synthesis and empirical evaluation. ***Review of Quantitative Finance and Accounting***, 2(2): 187-203.

Mulford, C. 1985. The importance of a market value measurement of debt in leverage ratios: replication and extensions. ***Journal of Accounting Research***, 23(2): 897-906.

Nekrasov, A., & Shroff, P. K. 2009. Fundamentals-Based Risk Measurement in Valuation. ***Accounting Review***, 84(6): 1983-2011.

Officer, M. S. 2007. The price of corporate liquidity: Acquisition discounts for unlisted targets. ***Journal of Financial Economics***, 83(3): 571-598.

Rubinstein, M. 1973. A mean-variance synthesis of corporate financial theory. ***The Journal of Finance***, 28(1): 167-181.

Schlueter, T., & Sievers, S. 2011. Determinants of market beta: the impacts of firm-specific accounting figures and market conditions. ***Review of Quantitative Finance and Accounting***: 1-36.

Van Dijk, M. A. 2011. Is size dead? A review of the size effect in equity returns. ***Journal of Banking & Finance***, 35(12): 3263-3274.

Vuolteenaho, T. 2002. What drives firm-level stock returns? ***The Journal of Finance***, 57(1): 233-264.

Wang, K., Li, J., & Huang, S. 2012. Bad beta good beta, state-space news decomposition and the cross-section of stock returns. ***Accounting & Finance***, 53(2): 587–607.

Table 1-1 Summary statistics

Panel A. Selected variables before the portfolio formation

Variable	mean	SD	min	p25	p50	p75	max
Sales	1,774	8,150	0	58	216	905	425,071
EBIT	236	1,344	-8,851	3	20	100	66,290
EBITDA	338	1,788	-7,236	6	30	146	78,669
Net Income	117	819	-29,580	1	9	50	45,220
Equity	968	4,657	0	39	130	501	211,686
Debt to Market Cap	0.53	0.84	0.00	0.03	0.23	0.67	9.94
Debt to Equity	0.68	0.93	0.00	0.07	0.40	0.92	9.95
Annual Stock Return	0.18	0.47	-1.03	-0.08	0.15	0.40	1.81
Book to Market	0.72	0.66	0.01	0.33	0.57	0.91	25.31

Panel B. Estimated variables

Variable	mean	SD	min	p25	p50	p75	max
β_j^{MKT}	0.97	0.16	0.54	0.87	0.97	1.06	1.63
β_j^{ACC}	0.40	0.40	-0.51	0.12	0.42	0.70	1.20
β_j^{PL}	1.04	0.19	0.51	0.93	1.04	1.14	1.73
β_{CFj}^{CFM}	0.77	0.23	0.36	0.63	0.77	0.89	1.32
β_{CFj}^{DRM}	0.23	0.20	-0.07	0.13	0.20	0.28	0.78
DOL	1.11	0.23	0.87	0.97	1.05	1.18	1.75
DFL	0.88	0.84	-2.70	0.92	1.00	1.14	1.62
GRWT	0.80	0.26	0.37	0.57	0.77	1.03	1.29

Table 1-1shows the summary statistics of the sample. SD is standard deviation, p25 is 25% quantil, p50 is the median, and p75 is 75% quantil. Panel A presents the descriptive firm-level statistics. Panel B presents the descriptive statistics of the calculated coefficients. β_j^{ACC} is the accounting beta. β_j^{PL} is the proxy levered beta. β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to *CF* News and *DR* News in the two-beta model, respectively. The three last rows correspond to the BOP model: *DOL* is the degree of operational leverage, *DFL* is the degree of financial leverage, and *GRWT* is Growth Beta. $\beta_j^{MKT}$is estimated using monthly data and used to compute PLB. Income statement numbers are in thousands.

Table 1-2 Risk premia estimates

VARIABLES	BACC $(\bar{r}_j)$	PLB $(\bar{r}_j)$	MTBM $(\bar{r}_j)$	BOP $(\bar{r}_j)$
β_j^{ACC}	0.18***			
	(0.031)			
β_j^{PL}		0.69***		
		(0.18)		
β_{CFj}^{CFM}			0.45***	
			(0.038)	
β_{CFj}^{DRM}			0.10**	
			(0.039)	
Log*(DOL)*				-0.35
				(0.52)
Log*(DFL)*				-0.98*
				(0.47)
Log*(GRWT)*				0.046
				(0.11)
Log*(ROE)*				0.75***
				(0.15)
Constant	0.070***	-0.57***	-0.18***	-0.34
	(0.019)	(0.19)	(0.029)	(0.29)
Observations	20	20	20	18

Table 1-2 presents the fitted results of equations (13) to (16), computing the implied risk of the studied models. β_j^{ACC} is the accounting beta (BACC). β_j^{PL} is the proxy levered beta (PLB). β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to *CF* News and *DR* News in the modified two-beta model (MTBM), respectively. Rows 5 to 8 correspond to the BOP model: *DOL* is the degree of operational leverage, *DFL* is the degree of financial leverage, and *GRWT* is Growth Beta. ROE is net income to book value of equity. The second row of each estimate reports the Standard errors (in parentheses), calculated by applying the Huber–White sandwich estimators.

*** p<0.01, ** p<0.05, * p<0.1

Table 1-3 Implied risk premiums generated for 40 B/E portfolios

VARIABLES	BACC $(\bar{r}_j)$	PLB $(\bar{r}_j)$	MTBM $(\bar{r}_j)$	BOP $(\bar{r}_j)$
β_j^{ACC}	0.17***			
	(0.024)			
β_j^{PL}		0.69***		
		(0.13)		
β_{CFj}^{CFM}			0.40***	
			(0.038)	
β_{CFj}^{DRM}			0.086**	
			(0.040)	
Log*(DOL)*				-0.00038
				(0.40)
Log*(DFL)*				0.62
				(0.43)
Log*(GRWT)*				-0.095
				(0.14)
Log*(ROE)*				0.95***
				(0.19)
Constant	0.084***	-0.56***	-0.14***	-0.058
	(0.017)	(0.13)	(0.027)	(0.30)
Observations	40	40	40	35

Table 1-3 presents the fitted results of equations (13) to (16), computing the implied risk of the studied models. β_j^{ACC} is the accounting beta (BACC). β_j^{PL} is the Proxy levered beta (PLB). β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to *CF* News and *DR* News in the modified two-beta model (MTBM), respectively. Rows 5 to 8 correspond to BOP model: *DOL* is the degree of operational leverage, *DFL* is the degree of financial leverage, and *GRWT* is Growth Beta. ROE is net income to book value of equity. The second row of each estimate reports the Standard errors (in parentheses), calculated by applying the Huber–White sandwich estimators.

*** p<0.01, ** p<0.05, * p<0.1

Table 1-4 Implied risk premiums using a subsample from 1970 to 2008

VARIABLES	BACC $(\bar{r}_j)$	PLB $(\bar{r}_j)$	MTBM $(\bar{r}_j)$	BOP $(\bar{r}_j)$
β_j^{ACC}	0.19***			
	(0.034)			
β_j^{PL}		0.72***		
		(0.17)		
β_{CFj}^{CFM}			0.45***	
			(0.037)	
β_{CFj}^{DRM}			0.093**	
			(0.039)	
Log*(DOL)*				-0.056
				(0.40)
Log*(DFL)*				-0.23
				(0.63)
Log*(GRWT)*				0.051
				(0.11)
Log*(ROE)*				1.07***
				(0.33)
Constant	0.074***	-0.59***	-0.18***	0.26
	(0.020)	(0.18)	(0.028)	(0.58)
Observations	20	20	20	18

Table 1-4 presents the fitted results of equations (13) to (16), computing the implied risk premium of the studied models. β_j^{ACC} is the accounting beta (BACC). β_j^{PL} is the proxy levered beta (PLB). β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to *CF* News and *DR* News in the modified two-beta model (MTBM), respectively. Rows 5 to 8 correspond to BOP model: *DOL* is the degree of operational leverage, *DFL* is the degree of financial leverage, and *GRWT* is Growth Beta. ROE is net income to book value of equity. The second row of each estimate reports the standard errors (in parentheses), calculated by applying the Huber–White sandwich estimators.
*** p<0.01, ** p<0.05, * p<0.1

Table 1-5. Forecasting ability of the studied methods

Panel A. Results using a 3-year forecasting window

	BACC	PLB	TBM
$\bar{r}_{09-11}$	0.83***	0.40*	0.93***
	(0.19)	(0.22)	(0.18)
Forecasting errors	17.5%	26.5%	9.5%

Panel B. Results using a 2 year forecasting window

	BACC	PLB	TBM
$\bar{r}_{09-10}$	0.55***	0.31	0.67***
	(0.18)	(0.19)	(0.16)
Forecasting errors	21%	29%	16%

Table 1-5 presents the results of a forecasting experiment. We use the estimates and the implied risk premia from 1970 to 2008 to forecast the returns from 2009 to 2011. Second row reports the Standard errors, calculated by applying the Huber–White sandwich estimators. Standard errors are in parentheses. Third row shows the output of ranking errors computed from equation 17.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1.

Compustat Items for variables calculation

Debt = current liabilities (Compustat item # 5) + long-term debt (# 9)

EBIT = Operating Income after Depreciation (# 178).

EBITDA = Operating Income before Depreciation (# 13) if available; otherwise, we use *EBIT* plus Depreciation and Amortization (# 14).

Book Value of Equity (BE) = Stock Holders Equity (# 144) - Preferred Stock + Deferred Taxes (if available) or

BE = Common Equity (# 60) + Preferred Stock or

BE = Total Assets (# 120) - Noncontrolling Interest (# 38) - Total Liabilities (# 75).

Preferred Stock is selected from the first non-missing option of redemption value (# 56), liquidating value (# 10), or book value (# 130).

Deferred taxes are taken from its book value (# 74) or Investment Tax Credit (# 208)

BE based on (Daniel and Titman, 2006), and (Cohen *et al.*, 2009).

Tax rate (τ) = USA top rate of statutory corporate taxes each year: 48% between 1972 and 1978, 46% from 1979 to 1986, 40% in 1987, 34% between 1988 and 1992, and 35% thereafter. Based on (Kemsley and Nissim, 2002)

Table 1-6 Summary of selected variables using a sample replication of BOP literature

Variable	N	mean	SD	min	p25	p50	p75	max
Sales	8,265	1,740	4,639	2	109	331	1,312	68,281
EBIT	8,265	174	499	0	9	31	123	7,815
EBITDA	8,263	239	647	0	12	43	173	9,043
Net Income	8,265	101	327	0	4	16	66	8,075
Equity	8,265	623	1,496	1	42	136	519	21,385
Debt to Market Cap	8,253	0.51	0.77	0.00	0.11	0.30	0.63	17.53
Debt to Equity	8,254	0.77	3.79	0.00	0.19	0.43	0.75	229.13
Annual Stock Return	8,264	0.19	0.40	-1.84	-0.03	0.17	0.39	4.17
Sales	8,265	1,740	4,639	2	109	331	1,312	68,281

Table 1-6 shows the summary statistics of the subsample that mimic the requirements requested of BOP-related literature. In this subsample, we include firms in the 'Manufacturing' sector, as defined by Fama-Frech 12 industrial-sector classification*. We also require strictly non-negative EBIT, EBITDA, and Net Income. SD is standard deviation, p25 is 25% quantil, p50 is the median, and p75 is 75% quantil. Panel A presents the descriptive firm-level statistics.

Table 1-7 Shapiro–Wilk normality test on the estimated variables

Variable	Obs	W	V	z	Prob>z
β_j^{MKT}	20	0.966	0.812	-0.421	0.663
β_j^{ACC}	20	0.991	0.221	-3.039	0.999
β_j^{PL}	20	0.953	1.121	0.230	0.409
β_{CFj}^{CFM}	20	0.963	0.878	-0.263	0.604
β_{CFj}^{DRM}	20	0.865	3.193	2.340	0.010
DOL	20	0.810	4.495	3.029	0.001
DFL	20	0.445	13.130	5.189	0.000
GRWT	20	0.956	1.035	0.069	0.472

Table 1-7 shows the output of the Shapiro–Wilk Normality Test on the estimated variables. β_j^{MKT} is the CAPM Beta. β_j^{ACC} is the accounting beta. β_j^{PL} is the proxy levered beta. β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to CF News and DR News in the two-beta model, respectively. The three last rows correspond to BOP model: DOL is the degree of operational leverage, DFL is the degree of financial leverage, and GRWT is Growth Beta. $\beta_j^{MKT}$is estimated using monthly data, and all other variables are estimated on an yearly basis.

Table 1-8 Standard errors from OLS regressions

VARIABLES	BACC $(\bar{r}_j)$	PLB $(\bar{r}_j)$	MTBM $(\bar{r}_j)$	BOP $(\bar{r}_j)$
β_j^{ACC}	0.18***			
	(0.031)			
β_j^{PL}		0.69***		
		(0.18)		
β_{CFj}^{CFM}			0.45***	
			(0.038)	
β_{CFj}^{DRM}			-0.10**	
			(0.039)	
Log*(DOL)*				-0.35
				(0.52)
Log*(DFL)*				-0.98*
				(0.47)
Log*(GRWT)*				0.046
				(0.11)
Log*(ROE)*				0.75***
				(0.15)
Constant	0.070***	-0.57***	-0.18***	-0.34
	(0.019)	(0.19)	(0.029)	(0.29)
Observations	20	20	20	18
Breusch–Pagan / Cook–Weisberg χ^2	0.97	0.5	0.96	36***

Table 1-8 presents the fitted results of equations (13) to (16), computing the implied risk premium of the studied models. β_j^{ACC} is the accounting beta (BACC). β_j^{PL} is the proxy levered beta (PLB). β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to CF News and DR News in the modified two-beta model (MTBM), respectively. Rows 5 to 8 correspond to BOP model: DOL is the degree of operational leverage, DFL is the degree of financial leverage, and GRWT is Growth Beta. ROE is net income to book value of equity. The second row of each estimate reports the standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 1-9 Standard errors using MacKinnon–White estimators

VARIABLES	BACC	PLB	MTBM	BOP
	$(\bar{r}_j)$	$(\bar{r}_j)$	$(\bar{r}_j)$	$(\bar{r}_j)$
β_j^{ACC}	0.18***			
	(0.031)			
β_j^{PL}		0.69***		
		(0.18)		
β_{CFj}^{CFM}			0.45***	
			(0.041)	
β_{CFj}^{DRM}			0.10**	
			(0.045)	
Log*(DOL)*				-0.82*
				(0.40)
Log*(DFL)*				-1.23
				(0.72)
Log*(GRWT)*				-0.063
				(0.14)
Log*(ROE)*				0.65***
				(0.15)
Constant	0.070***	-0.57***	-0.18***	-0.52
	(0.019)	(0.20)	(0.031)	(0.30)
Observations	20	20	20	18
R-squared	0.568	0.403	0.940	0.851

Table 1-9 presents the fitted results of equations (13) to (16), computing the implied risk premium of the studied models. β_j^{ACC} is the accounting beta (BACC). β_j^{PL} is the proxy levered beta (PLB). β_{CFj}^{CFM} and β_{CFj}^{DRM} are the cash flow reactions to CF News and DR News in the modified two-beta model (MTBM), respectively. Rows 5 to 8 correspond to BOP model: DOL is the degree of operational leverage, DFL is the degree of financial leverage, and GRWT is Growth Beta. ROE is net income to book value of equity. The second row of each estimate reports the standard errors (in parentheses), calculated by applying the MacKinnon–White estimators.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

PAPER 2.

Presented at 19th Annual Conference of the Multinational Finance Society (Izmir, Turkey, July 2013).

Unlevered betas and the cost of equity capital: an empirical approach[1].

2.1 Introduction

Since the publication of the seminal paper by Hamada (1972) on the role of financial leverage in the computation of systematic risk and the development of unlevered betas (*βu*), this concept has drawn the attention of researchers and practitioners in different ways. On the one hand, researchers have increased discussions on the correct rate at which to discount tax shields from financial debt, thereby leading to multiple, contradictory models to calculate *βu*. On the other hand, practitioners have been concerned about how to utilise the basic idea behind *βu* to resolve the lack-of-information problem to calculate the cost of capital for non-traded firms and individual business units. However, there have been few efforts to empirically examine how relevant or effective these approaches might be.

The present study aims to fill this research gap, and thus contributes to the literature in two ways. First, it empirically tests a theoretical model for unlevered betas. However, instead of assessing *βu* directly, we develop a model with two predicted targets that allows us to test contradictory versions of this measure of systematic risk. Second, this study evaluates the performance of *βu* to check the robustness of practitioners' methodologies, as we believe that the true importance of unlevered betas rests in their application in calculating the cost of equity capital for non-traded firms.

We analytically derive the predicted values of two components in our model; namely, the proxy levered beta (PLB), and the discrepancy term (λ). First, the PLB is the resulting value of a three-step process in which we (i) unleverage all market-based beta (BMKT; denoted by β_m) values; (ii) calculate the exogenous yearly mean for each

[1] Sarmiento-Sabogal, Julio and Sadeghi, Mehdi. Candidate contribution: data collection, literature review, research design and analysis of results, which account for about 90% of the paper. The co-author have contributed with his comments and corrections of the paper.

industry[2]; and (iii) calculate the PLB by levering the unlevered industry beta with the individual leverage ratio of each firm. Following Hamada (1972), we expect the PLB to be equal to the BMKT. Second, λ, which comprises all market disturbances and risk-class misspecifications, is calculated by dividing the exogenous yearly sector mean by the individual βu. Therefore, in a "perfect" risk classification without any market disturbances, the exogenous yearly sector mean and βu should move towards the same value, and λ should approach to the unity.

We address the theoretical discussion on the impact of corporate taxes (denoted by τ) on βu by decomposing the calculation of systematic risk. There are two contrasting arguments in the literature about the appropriate assumptions for decomposing systematic risk[3]. Fernandez (2004, 2005, 2007), and Massari *et al.* (2008) agree with the assumptions made by Modigliani and Miller (1958–1963) (MM hereafter) that (i) the absolute value of debt does not change over time, and (ii) that the correct rate to discount tax shields is the cost of debt *(Kd)*. In contrast, following Miles and Ezzell (1985) (ME hereafter), another group of authors[4] consider that the absolute value of debt changes periodically to maintain a target leverage ratio, and that the correct rate to discount tax shields from the first period is the cost of unlevered equity. We find that the assumptions of the MM approach are statistically more robust than are those of the ME approach. Nevertheless, both approaches tend to overestimate systematic risk because the market average of the (recalculated) PLB is above the BMKT.

The remainder of this paper is structured as follows. Section 2.2 presents the unlevered betas, and the method to calculate a proxy of the BMKT using such metrics. Section 2.3 develops our testing model. Section 2.4 describes the dataset and methodology. Section 2.5 presents the empirical results. Section 2.6 examines the robustness of our results, and Section 2.7 concludes.

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[2] The exogenous mean for each firm corresponds to the average of all year-sector observations, excluding its own observation. This calculation method avoids possible endogeneity issues and mimics the practitioners' calculation of the PLB for non-traded firms.

[3] Other arguments that are not studied in this paper include those put forward by Harris and Pringle (1985), Fernandez (2002), and Kolari and Velez-Pareja (2012).

[4] See, for example, Taggart (1991), Arzac and Glosten (2005), Fieten *et al.* (2005), and Cooper and Nyborg (2006).

2.2 Unlevered betas and proxy methods

According to the MM theory, firm value (V_L) in the absence of bankruptcy costs is a function of its own hypothetical value based on non-debt financing (V_U), and the present value of the effect of tax shields (*VTS*) produced by the financial debt. Thus,

$$V_L = V_U + VTS \tag{2.1}$$

As an implication of the MM theory, Hamada (1972) defines the relationship between systematic risk and leverage as $\beta m = \beta u / \left(EL / Eu \right)$, where *EL* is the market value of levered common equity, and *Eu* is the expected market value of unlevered common equity. Rubinstein (1973) extended the Hamada model by incorporating the impacts of corporate taxes (τ) and the market value of debt *(D)* on the beta, as follows:

$$\beta u^{MM} = \beta m \Big/ \left[1 + \left(D / E_L \right)\left(1 - \tau \right) \right] \tag{2.2}$$

ME argue that equation (2.2) implies a constant debt, which might not be realistic because of the stochastic behaviour of the firm value. Therefore, they set a constant leverage ratio rather than a constant (known) value of debt. They assume that the absolute value of debt is adjusted over time according to the future values of the firm. Additionally, equation (2.2) assumes that the correct discount rate for *VTS* in (2.1) is the cost of debt (K_d)[5].

An alternative model suggested by Bowman (1980) is based on the following equation:[6]

$$\beta u^{ME} = \beta m \Big/ \left(1 + D / E_L \right) \tag{2.3}$$

Although the only difference between equations (2.2) and (2.3) is the use of tax shields, the extensive discussion regarding which is the correct model to calculate the unlevered betas has been inconclusive. Fernandez (2004, 2005, 2007) and Massari *et al.* (2008), among others, support the underlying assumptions made in (2.2), while Arzac and Glosten (2005), Cooper and Nyborg (2006), Fieten *et al.* (2005), and Tham and Vélez-Pareja (2004) argue that (2.3) is the correct derivation of *βu*. However, these

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[5] Tham and Vélez-Pareja (2004) offer a detailed explanation about this assumption.

[6] Bowman's (1980) definition of βu can also be derived from ME assuming constant growth.

studies have largely been limited to theoretical issues, with little reference to the empirical implications of this conundrum. This has been followed by a number of empirical studies on this subject that have used either equation (2.2) and (2.3), and which have paid little attention to the theoretical issues at hand[7].

On the other hand, practitioners calculate the cost of equity capital (*Ke*) using either equation (2.2) or (2.3) as a proxy method for non-traded firms or individual business units. In this technique, *Ke* is computed using the average of the industry sector unlevered beta $\left(\overline{\beta u}\right)$, and a new PLB $\left(\beta l\right)$ is recalculated using the leverage of the unlisted company. That is,

$$\beta l = \overline{\beta u}\,\left[1+\psi\right] \tag{2.4}$$

where Ψ represents the correct relationship between the leveraged ratio (L) and the systematic risk. Thus, $\Psi = L$ for ME and $\Psi = L*(1-\tau)$ for MM.

2.3 Corporate taxes and systematic risk

The tax rate has a diminishing effect on the decomposition of systematic risk. Without corporate taxes, there would be no conflict between the MM and ME approaches (equations (2.2) and (2.3)). When the tax rate is more than zero, then the βu values that are estimated according to the MM model are higher compared with those from the ME model. However, the argument regarding which model is more accurate cannot be resolved through an empirical test because of the absence of a target (e.g., the market value of an unlevered listed firm[8]). As a result, the discussion about differences between the two models has been confined to theoretical arguments on their underlying assumptions.

We define the PLB as our target so as to evaluate the empirical performances of the MM and ME approaches. This PLB is the value that results from the following three-step unleveraged/leveraged process. First, we compute individual unlevered betas for each firm-year in the sample. Second, we compute the exogenous yearly mean of

[7] See, for example, Marston and Perry (1996), Kemsley and Nissim (2002), Bowman *et al.* (2005), and Bowman and Bush (2006).

[8] In our sample, there are some observations with these characteristics. However, the number is not significantly large enough to be able to form a meaningful sample to study.

unlevered betas for each industry sector. Third, we estimate the PLB for firms using the average beta of their industry sector, and their individual leverage ratios. In the absence of any market imperfections or grouping errors, we expect two features from the PLB: (i) the PLB is hypothesised to be equal to the BMKT at the individual (firm) level; and (ii) the average of all PLBs is hypothesised to be equal to the average of the BMKTs at a market level.

To discuss the idea further, consider the average unlevered beta $\overline{\beta u}$ for a group of firms in the same risk class during a given period of time:

$$\overline{\beta u} = (1/n) * \sum_{i=1}^{n} \beta m_i \Big/ (1+\psi_i) \tag{2.5}$$

where $\Psi = L$ for ME and $\Psi = L*(1-\tau)$ for MM. In the absence of market imperfections, all unlevered betas in the same risk class should be equal (Hamada, 1972). Thus, (2.5) becomes $\overline{\beta u} = \beta m_i / (1+\psi_i) = \beta u_i$ for all firms (i) in the same risk class[9]. Although an industry sector might be considered as a proxy for a risk class, it is not realistic to assume that all unlevered betas in the same industry sector are equal. Therefore, let λ_i be a discrepancy term that comprises all market disturbances and risk-class misspecifications, defined as:

$$\lambda_i = \overline{\beta u} / \beta u_i \tag{2.6}$$

Using λ_i, the relationship (2.5) can be redefined as:

$$\overline{\beta_U} = \beta m_i / (1+\psi_i) * \lambda_i \tag{2.7}$$

Using the practitioners' approach (equation (2.4)), we calculate a general expression for the PLB (denoted by *βl)* for any firm in a specific industry sector at a given period of time:

$$\begin{aligned} \beta l_i &= \overline{\beta u} * (1+\psi_i) \\ &= \frac{\beta m_i}{(1+\psi_i)} * \lambda_i * (1+\psi_i) \\ &= \beta m_i * \lambda_i \end{aligned} \tag{2.8}$$

[9] In our empirical model, we operationalize an exogenous mean of an unlevered beta as: $\overline{\beta u_j} = \left[1/(n-1)\right] * \left[\sum \beta u_i - \beta u_j\right]$, where βu_j is the unlevered beta of a firm j in the risk class i.

From (2.8), we can establish that the expected value of the PLB is the same as the BMKT in the absence of both market disturbances and risk-class misspecifications ($\lambda_i = 1$). We use (2.8) to empirically test the MM and ME models as well as the practitioners' approach so as to calculate systematic risk using the PLB.

2.4 Dataset and methodology

2.4.1 Dataset

We start calculating the BMKT from a panel composed of 643,317 firm-month observations of US listed companies in the period from 1970 to 2011 retrieved from the Center for Research in Security Prices (CRSP). Each firm is required to have at least 60 consecutive observations. We merge the monthly market information with the annual financial information for each firm, obtained from COMPUSTAT averaging of BMKTs and market capitalization. Those firms whose fiscal year end did not fall on December were excluded from our sample. The merged dataset used in this study contains 55,357 firm-year observations of companies with a positive value of equity.

Table 2-1 presents the descriptive statistics for the entire sample of companies used in this study. It examines the accounting fundamentals, the firms' debt over the market value of equity and debt over the book value of equity (*BE*) ratios, as well as the market information of the firms across all industries during the estimation period of 1970–2011. Panel A shows the yearly financial fundamentals, while Panel B presents monthly market excess returns. Firms are divided according to the Fama–French 12-industry-sector specification[10]: consumer non-durables (1), consumer durables (2), manufacturing (3), energy (4), chemicals (5), business equipment (6), telecommunications (7), utilities (8), retail (9), healthcare (10), financial (11), and others (12). Market value is calculated as the closing price at the end of each month, multiplied by the number of outstanding shares. The *BE* is defined as the stockholders' equity, plus deferred taxes, minus preferred stock[11]. Debt is defined as debt held in current liabilities plus long-term debt.

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[10] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[11] Section 2.4.2 contains a detailed explanation of the *BE* estimation.

The results in Panel A of Table 2-1 show that the overall leverage ratio based on the market value of equity is 67%, with a standard deviation of 132%. The overall leverage ratio based on the *BE* is 91%, with a standard deviation of 190%. The lower leverage ratio based on the market value of equity when compared to the *BE* is an indication of a considerable increase in the market value of equity after the initial public offering of shares.

Further observation of the summary statistics suggests that there are significant differences in the magnitude of the accounting and financial variables across industrial sectors. For instance, with respect to the energy sector, the average *BE* and market capitalization is almost four times larger than the overall sample mean, indicating that firms in this sector are larger than in the other individual sectors. We also find that the leverage ratios of the energy and financial sectors are nearly twice as large as the mean of the leverage ratio for other sectors. Further details on this issue will be covered in Section 6.1.

The results in Panel B of Table 2-1 indicate that the general mean of the monthly excess return is 1.47%, which is not significantly different to the individual industrial averages. The overall standard deviation for the full sample is 15.09%. These summary statistics are similar to those reported in previous studies (see, for example, Cohen, Polk, & Vuolteenaho, 2009; and Fama & French, 2008).

2.4.2 Methodology

The empirical analysis is carried out in four steps. First, we compute the BMKT using a value-weighted portfolio. Second, we calculate the exogenous yearly mean of the unlevered beta. Third, we compute the PLB of each firm using its unlevered sector beta. Finally, we run panel regressions between the BMKT and PLB.

<u>*BMKT*</u>

We use firms' excess returns *(R_i,),* calculated as the difference between the company return and the one-month T-bill return. We obtain the monthly BMKT for each firm using individual excess market returns from the 60 previous months[12] by using the standard model: $\beta m = \sigma\left(R_i, R_m\right)/\sigma^2\left(R_m\right)$, where R_m is the excess return of a value-

[12] An alternative (untabulated) version using 12 months essentially confirms our results.

weighted portfolio calculated by Keneth French[13], $\sigma(R_i, R_m)$ is the covariance of stock returns and market returns, and $\sigma^2(R_m)$ is market variance. We obtain a matrix with monthly β_m values for each company between 1975 and 2011. Note that observations from 1970 to 1974 are required to compute the first BMKT. We dropped observations with negative betas, and we winsorized at the 99% percentile grouping for each industrial sector.

The unleveraged process and the PLB

We use equations (2.2) and (2.3) to calculate an exogenous mean for each firm, by including the information for all firms in the same sector year, except for its own observation. This procedure implies that there are as many averages as the number of firms in each specific sector year. The estimation of the exogenous mean helps us to avoid any possible endogeneity issues in our data sample. Additionally, this procedure is equivalent to the one employed by the unlisted firms, which have to rely on the information gathered from public firms to compute PLBs.

Although the theory recommends using the market prices of debt and equity as the correct measure for leverage (i.e., *D/E*), the estimation of the market value of debt demands an enormous amount of additional work. So, we use the book value as a proxy for the market value of debt. This procedure is not likely to adversely affect our study. According to Bowman (1980), and Mulford (1985), the book value is a good substitute for the market value of the debt at the firm level. Debt (*D*) in our study is the summation of the current liabilities plus long-term debt. Following Kemsley and Nissim (2002), we define corporate taxes as the top rate of statutory corporate taxes each year[14]. We use two definitions of leverage: *D/E* and *D/BE*. The latter corresponds to the use of the *BE* instead of the market value, as used by practitioners for non-traded firms.

Similar to Daniel and Titman (2006), and Cohen *et al.* (2009), *BE* is estimated as stock holders' equity minus preferred stock, plus deferred taxes (if available). If stockholders' equity is missing, we compute this figure as common equity plus preferred stock, or total assets minus non-controlling interest minus total liabilities. Preferred stock is selected from the first non-missing option of the redemption value,

[13] We use the Rm-Rf component of the Fama–French factors, as updated by Keneth French.

[14] In the USA, the top rate of statutory corporate taxes was 48% between 1972 and 1978, 46% from 1979 to 1986, 40% in 1987, 34% between 1988 and 1992, and 35% thereafter.

liquidation value, or book value. Deferred taxes are taken from the book value, or from the investment tax credit.

We obtain four alternative definitions of the PLB. βl_{E}^{MM} and βl_{BE}^{MM} represent the unleveraged and leveraged processes according to the MM approach (equation (2.2)), using the market value and *BE*, respectively. βl_{E}^{ME} and β_{BE}^{ME} correspond to the resulting PLB from the unleveraged/leveraged process in equation (2.3), again using either the market value or *BE*, respectively. *D/E* and *D/BE* are winsorized at the 99% percentile grouping for industrial sector[15].

This methodology helps us to mimic the use of the PLB for the valuation of unlisted firms in a number of ways: First, we include book values as proxies for market values of debt and equity within the PLB calculation. This procedure allows us to test the PLB's performance in the absence of market information, as is usual for unlisted firms. Second, we compute the exogenous mean that excludes the information of each individual company. This technique replicates the common problem of unlisted firms, which must rely on information gathered from public firms to enable the computation of the PLB. Third, unlike the majority of previous studies, we include small cap stocks within our sample. This decision implies that we have to deal with a great amount of noise generated for these companies; however, their exclusion reduces the potential usefulness of the results, because a significant proportion of unlisted firms are also small. Finally, we do not use any portfolio aggregation to test our results. The decision to conduct regressions at firm level rather than portfolio level adds noise to our results, but allows us to derive conclusions on the same scale as the PLB, which is more useful for practitioners.

To summarise, we calculate the BMKTs for each firm year and then we unleverage the betas using the specific leverage of the firm. We next calculate the exogenous mean of the unleveraged betas for each firm year, and finally we recalculate the PLB for each firm year, again using the specific leverage of the firm. Therefore, we obtain the following four versions of the PLB for each version of the BMKT:

$$\beta l = \beta l_{BE}^{MM} = \overline{\beta u_{E}^{MM}}\left[1+\left(D/BE\right)\left(1-\tau\right)\right] \tag{2.9}$$

$$\beta l = \beta l_{E}^{MM} = \overline{\beta u_{E}^{MM}}\left[1+\left(D/E\right)\left(1-\tau\right)\right] \tag{2.10}$$

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[15] As the left-hand tail of the PLB distribution is truncated for the positive *BE* requirement.

$$\beta l = \beta l_{BE}^{ME} = \overline{\beta u_E^{ME}}\left[1+\left(D / BE\right)\right] \tag{2.11}$$

$$\beta l = \beta l_{E}^{ME} = \overline{\beta u_E^{ME}}\left[1+\left(D / E\right)\right] \tag{2.12}$$

where $\overline{\beta_E^{MM}}$ and $\overline{\beta_E^{ME}}$ are the exogenous means of the unlevered beta using the MM and ME model, respectively. *D/E* and *D/BE* correspond to the market value and *BE*, respectively.

Table 2-2 presents the summary statistics of the calculated coefficients. The BMKT (βm) for each firm is calculated using the individual market returns from the previous 60 months. βu is the unlevered beta calculated using equations (2.2) and (2.3). βl is the PLB, and its values are estimated according to equations (2.9) to (2.12). λ is the discrepancy term in the unleveraged/leveraged process (defined by equation (2.6)).

The estimated BMKT average of 1.09 in Table 2-2 is slightly higher than the theoretical value of 1.00. A possible explanation for this discrepancy is that as we are not using any sort of portfolio aggrupation, the influence of the small cap stocks may have increased this average. The noise produced in the time series (within) dimension of the BMKT is lower than the cross-sectional (between) dimension. This indicates that volatility among the firms is higher than the variation across time. However, this also raises a warning flag about how the use of this shared information may affect our results[16]. This issue is tested in Section 2.6.3.

The PLB estimates in Table 2-2 (from $\beta l_E^{MM} = 1.18$ to $\beta l_{BE}^{ME} = 1.45$) are higher than the theoretical expectation as they should be equal to the BMKT. Equation (2.8) implies that the PLB is equal to the BMKT when λ is equal to one. However, the estimated λ is slightly higher than unity because $\overline{Bu}$ tends to diminish the effect of observations with a high leverage ratio. Further, the results using book values are smaller than those where market values are employed. This is unsurprising, since the average of the market value of equity is greater than its corresponding book value. Therefore, the factor (1+ D/E) in equations (2.2) and (2.3) tends to be greater than the (1+ D/BE) value in equations (2.9) to (2.12). Although we obtained the result βu^{MM} > βu^{ME}, as predicted by the ME, this inequality is reversed for the PLB, as explained in

[16] This problem arises when we calculate our coefficients with a firm-month base, using information from the previous 60 months. For example, the market returns obtained in January 1980 are needed to compute βm from the same period to December 1984.

Section 3. The discrepancy term (λ) takes the expected value of one, but contains a great amount of noise.

<u>*Panel regression issues*</u>

Recent literature has criticized the selection of the regression model for longitudinal financial datasets (Gow *et al.*, 2010; Petersen, 2009; Thompson, 2011). These critics have signalled that some common methods to compute the standard errors seem to be biased due to the failure to adjust for possible correlation in both the time series and cross-sectional dimensions of the panel. There are several ways to sort out this issue. For example, previous authors often compute Newey and West (1987) or Fama and MacBeth (1973) estimators; however, these methods might produce biased estimations with cross-sectional dependence (Gow *et al.*, 2010). Another common way to solve the problem is by calculating a fixed-effects regression including dummy variables for the years. Nevertheless, this computation caused over-optimistic regression results in our sample. Since we have an unbalanced panel, it is possible to use the Driscoll and Kraay (1998) estimation and adjust the autocorrelation by using the Newey–West correction, as suggested by Hoechle (2007). Yet, the asymptotic assumption of this model might be unfeasible with the (relatively) small size of the time dimension in our sample. Therefore, we choose a two-dimensional clustered regression correcting for heteroskedasticity. There is a common agreement in the relevant literature about its robustness for multidimensional dependence. Additionally, this estimation method seems to provide us with conservative regression estimates[17].

2.5 Empirical results

Table 2-3 presents the results of the two-dimensional clustered regression, which is robust to both serial and cross-sectional correlation, as proposed by Cameron *et al.* (2006), and Petersen (2009). Standard errors are calculated using Huber–White sandwich estimators to correct for heteroskedasticity. We also include dummies for each

[17] Nevertheless, our findings are robust to changes in any of the standard error computations. Tables 2.8 to 2.11 in Appendix 2 show the results of the other described regression methods.

industry sector to control for possible co-movements across firms in the same industry (not tabulated). Thus, the following model is estimated:

$$\beta l_{it} = \alpha_1 + \alpha_2 \beta m_{it} + \alpha_3 \lambda_{it} + \alpha_4 I' + \varepsilon_{it} \tag{2.13}$$

where βl denotes the PLB. BMKT is the βm. Vector I' contains dummies for each industrial sector. This regression model is applied to each PLB specification in equations (2.9) to (2.12).

The results in Table 2-3 indicate that the coefficients for BMKT (α_3) based on BE ($\alpha_3, \beta l_{BE}^{MM} = 1.06$; $\alpha_3, \beta l_{BE}^{ME} = 1.28$) are higher than the estimates based on E ($\alpha_3, \beta l_{E}^{MM} = 0.89$; $\alpha_3, \beta l_{E}^{ME} = 1.04$). This figure confirms our previous findings in that by using BE, the PLB tends to be overestimated. All of these coefficients are close to the expected value of one[18], and they are significantly correlated to the PLB at the 1% level. This result is an indication that the PLB might be a good substitute for the BMKT. The discrepancy error (α_4) has a negative effect on the PLB, with the estimated coefficients of approximately one in three out of four studied PLB models ($\alpha_4, \beta l_{BE}^{MM} = -1.11$; $\alpha_4, \beta l_{BE}^{ME} = -0.95$; $\alpha_4, \beta l_{E}^{MM} = -1.326$; $\alpha_4, \beta l_{E}^{ME} = -1.11$). Coefficients for λ are also correlated with the BMKT in all PLB specifications at the 1% level, indicating that λ comprises information that is missing from the PLB results. This outcome confirms that the industrial sector is an accurate proxy of the risk class, but other factors than industry and leverage influence systematic risk. The results provide further evidence that PLBs calculated as based on the book value of debt show weaker relationships to those calculated based on the market value of debt. This is consistent with the findings of Bowman (1980), and Mulford (1985). Finally, in line with Don (1982), our regression estimates highlight how the PLB using the MM model has a stronger relationship with the BMKT than the results based on the ME approach. Although this finding is not entirely conclusive, it contradicts the ME warnings about the over-calculation of risk when using the MM version for leverage decomposition. The next section is devoted to this issue.

[18] Note that this expectation arises from our hypothesis that under certain conditions, the PLB is equal to the BMKT in equation (2.8). Consequently, the slope α_3 in the equation should be around one.

2.5.1 Comparing the empirical performances of the MM and ME models

The present section aims to verify whether a larger mean computed via the ME proxy model is a signal for less significant results compared to those obtained using the MM model. If the PLB using the ME model overestimates systematic risk, it may indicate that the cost of equity capital when using such a method is also overestimated. We run the *Wilcoxon signed-rank* test on the pooled sample to verify this hypothesis using the models specified in the equations. First, we test the null hypothesis: BMKT = PLB. The results in Panel A of Table 2-4 indicate that this hypothesis is rejected, since all the differences are significant at the 1% level. The estimates obtained from ME ($\beta l_E^{ME} = -38.28$) are more negative than those obtained from MM ($\beta l_E^{MM} = -30.72$), indicating that the latter model tends to overestimate the systematic risk more than the former one. Consistent with previous findings, these figures based on E are lower than the estimates based on BE ($\beta l_{BE}^{ME} = -73.91$; $\beta l_{BE}^{MM} = -60.25$), confirming that BE amplifies the errors in the unleveraging/leveraging process.

With the confirmation that the PLB produces higher values than the BMKT, we further test the null hypothesis $\beta^{MM} = \beta^{ME}$ directly. Our findings in Panel B of Table 2-4 indicate that this hypothesis is significantly rejected for both unlevered betas and the PLB. As signalled by the ME model, the estimated unlevered betas using the MM model are higher since the coefficient of the difference is positive and significant ($\beta u = 203.13$). However, with no theoretically predicted value to use as a target for comparing unlevered betas, we cannot draw any meaningful conclusions from this finding. On the other hand, the coefficient for the PLB ($\beta l_E = -46.95$) suggests that the ME-obtained values are significantly higher than those obtained when using the MM model. In fact, the negative sign of the z-statistic suggests that the ME proxies tend to be higher. This shows that using the ME model tends to overestimate systematic risk more so than when using the MM model.

2.6 Robustness checks

Although the results presented in Section 2.5 allow us to draw a general conclusion about the empirical validity of the unleveraged/leveraged process for our sample, the outcome of the empirical findings may differ depending on a number of factors. We can thus examine the robustness of these results by: (i) analysing the validity of the unleveraged/leveraged process for each sector (Section 6.1), (ii) testing the regression across different periods of time (Section 6.2), and (iii) analysing possible endogeneity issues (Section 6.3).

2.6.1 The effect of the financial and the utilities industrial sectors

We investigate whether our findings might be affected due to the inclusion of the financial and utilities sectors in the sample. These industries are excluded from some empirical research[19] due to their specific financial characteristics. In Section 2.4 we already pointed out some of the differences in the accounting fundamentals of these two sectors compared to others. Consequently, we estimate the model in equation (2.13) by using a subsample that excludes firms in both of these industrial classifications. The outcome, reported in Table 2-5, indicates that we can eliminate this concern, since all versions of the PLB are statistically correlated with the BMKT at the 1% level.

Further, we investigate whether the Fama–French 12–industrial–sector specification is a good proxy for risk-class classification. If this classification is correct, then the level of systematic risk measured as the BMKT should be different across all sectors. Consequently, we run the *Kruskal–Wallis* test on the BMKT in the pooled sample. The test results (H (11) = 9707, p < .001) indicate significant differences among the twelve sampled industrial sectors.

2.6.2 Regression results in subsamples

Another concern in terms of the validity of our findings is whether the sample period affects the outcome, especially because our results show a stronger link between the PLB and BMKT than do previous studies. Table 2-6 presents the results when the sample is divided into two subsamples: 1975 to 1990 and 1991 to 2011. Although the t-statistics are lower than those obtained from the full sample, the statistical significance is still high for both subsamples, suggesting that our results are robust for different sample periods.

[19] See for example: Kemsley and Nissim (2002); Li and Zhao (2008); Marston and Perry (1996); Wang *et al.* (2009).

2.6.3 Endogeneity issues

Previous studies in this field do not have the problem of shared information because the use of cross-sectional analysis avoids the use of rolling betas. Instead, our panel requires the computation of BMKT coefficients based on monthly rolling regressions, implying that each estimate shares 59 observations with the previous one. Additionally, the calculation of the five-year averaged debt to equity ratio (*D/E*) is another possible source of endogeneity. Therefore, we create a subsample by dropping all years but 1975 and the further multiples of five (i.e. 1980, 1985, etc.). This approach does not share information in either the monthly (BMKT) or the yearly calculations (PLB). The regression results in Table 2-7 show that our results are robust to this possible issue**.**

2.7 Conclusions

The present paper used unlevered betas to empirically test two important issues in systematic risk decomposition by leverage. We adopted the two most common definitions of unlevered betas, and assessed the validity of the practitioners' methods to determine the cost of equity capital for unlisted companies. We created an analytical model with two theoretically predicted components. The first component was the proxy levered beta (PLB). This value was based on a three-step unleveraged/leveraged process in which we: (i) unleveraged all market-based beta (BMKT) values, (ii) calculated the exogenous yearly mean of each industry sector, and (iii) measured the PLB by leveraging the unlevered industry sector beta by using the individual leverage ratio of each firm. The second component in our model was the discrepancy term (λ), which comprises all market disturbances and risk-class misspecifications. λ is defined as the ratio of the exogenous yearly mean of each industry sector on the individual, unlevered beta value. Following Hamada (1972), we expected the PLB to be equal to the BMKT, and λ to approach the value of one.

Our estimates indicate that the PLB is highly correlated with the BMKT, even when we replace the market value of equity with the book value. These results are in line with previous findings (Bowman, 1980; Kemsley & Nissim, 2002; Bowman & Bush, 2006). However, PLB tends to overestimate the systematic risk when is compared with BMKT, as pointed out by Faff *et al.* (2002) and Marston and Perry (1996). Unlike earlier studies, we imitated specific procedures used by practitioners to calculate the cost of capital for unlisted firms. Our study also applied a longitudinal method that permits analysis over a comprehensive timescale rather than using only selected points in time. Nevertheless, the finding that λ was significantly related to the BMKT demonstrates that this term contains information affecting the systematic risk beyond leverage and the industrial-sector classification. This finding suggests that further research is needed to compare this decomposition method with others, including accounting-based betas, and operational-based betas.

In addition, we found that between the two contradicting theoretical models of the PLB, the approach proposed by MM, in which tax shields are included in the unleveraged/leveraged process, showed the best statistical performance. The dominance of the MM over the ME approach was reconfirmed when we used book value rather than market value of equity in the PLB calculation. These findings imply that the financial market tends to use the cost of debt instead of the unlevered cost of capital to discount tax shields.

Finally, our results suggest that the use of the PLB to solve the lack of market information for both non-traded firms and individual business units is not misleading, even when applying the book value of debt rather than the market value. Although the relationship between the PLB and BMKT is stronger for the market value of equity, book values also show statistically significant correlations. This represents good news for practitioners, who have long used the unleveraged approach despite little empirical support for the validity of their procedures.

2.8 References

Arzac, E., & Glosten, L. 2005. A reconsideration of tax shield valuation. ***European Financial Management***, 11(4): 453-461.

Bowman, R. 1980. The importance of a market-value measurement of debt in assessing leverage. ***Journal of Accounting Research***, 18(1): 242-254.

Bowman, R., & Bush, S. 2006. Using comparable companies to estimate the betas of private companies. ***Journal of Applied Finance***, 16(2): 71-81.

Bowman, R., Bush, S., & Graves, L. 2005. Estimating betas using comparable company analysis: is it a reliable method? ***JASSA***(1): 10-12,14,23.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. 2006. Robust Inference with Multi-way Clustering. ***National Bureau of Economic Research Technical Working Paper Series***, No. 327.

Cohen, R., Polk, C., & Vuolteenaho, T. 2009. The price is (almost) right. ***Journal of Finance***, 64(6): 2739-2782.

Cooper, I., & Nyborg, K. 2006. The value of tax shields is equal to the present value of tax shields. ***Journal of Financial Economics***, 81(1): 215-225.

Daniel, K., & Titman, S. 2006. Market reactions to Tangible and intangible information. ***The Journal of Finance***, 61(4): 1605-1643.

Don, M. C. 1982. Evidence on a simplified model of systematic risk. ***Financial Management***, 11(3): 53-63.

Driscoll, J. C., & Kraay, A. C. 1998. Consistent covariance matrix estimation with spatially dependent panel data. ***Review of Economics and Statistics***, 80(4): 549-560.

Faff, R. W., Brooks, R. D., & Kee, H. Y. 2002. New evidence on the impact of financial leverage on beta risk: a time-series approach. ***The North American Journal of Economics and Finance***, 13(1): 1-20.

Fama, E. F., & French, K. R. 2008. Dissecting anomalies. ***The Journal of Finance***, 63(4): 1653-1678.

Fama, E. F., & MacBeth, J. D. 1973. Risk, return, and equilibrium: empirical tests. ***Journal of Political Economy***, 81(3): 607-636.

Fernandez, P. 2002. The correct value of tax shields. ***Unpublished paper. IESE Business School. Available at 10.2139/ssrn.330541***.

Fernandez, P. 2004. The value of tax Shields is not equal to the present value of tax shields. ***Journal of Financial Economics***, 73(1): 145-165.

Fernandez, P. 2005. Reply to "comment on the value of tax shields is not equal to the present value of tax shields". ***The Quarterly Review of Economics and Finance***, 45(1): 188-192.

Fernandez, P. 2007. A more realistic valuation: adjusted present value and WACC with constant book leverage ratio. ***Journal of Applied Finance***, 17(2): 13-20.

Fieten, P., Kruschwitz, L., Laitenberger, J., Löffler, A., Tham, J., Vélez-Pareja, I., & Wonder, N. 2005. Comment on "the value of tax shields is not equal to the present value of tax shields". ***The Quarterly Review of Economics and Finance***, 45(1): 184-187.

Gow, I., Ormazabal, G., & Taylor, D. 2010. Correcting for cross-sectional and time-series dependence in accounting research. ***Accounting Review***, 85(2): 483-512.

Hamada, R. S. 1972. The effect of the firm's capital structure on the systematic risk of common stocks. ***The Journal of Finance***, 27(2): 435-452.

Harris, R. S., & Pringle, J. J. 1985. Risk-adjusted discount rates-extensions from the average-risk case. ***Journal of Financial Research***, 8(3): 237.

Hoechle, D. 2007. Robust standard errors for panel regressions with cross-sectional dependence. ***Stata Journal***, 7(3): 281-312.

Kemsley, D., & Nissim, D. 2002. Valuation of the debt tax shield. ***Journal of Finance***, 57(5): 2045-2073.

Kolari, J. W., & Velez-Pareja, I. 2012. Corporation income taxes and the cost of capital: a revision. ***Innovar - Revista de Ciencias Administrativas y Sociales***, 22(46): 53-71.

Li, K., & Zhao, X. 2008. Asymmetric information and dividend policy. ***Financial Management***, 37(4): 673-694.

Marston, F., & Perry, S. 1996. Implied penalties for financial leverage: theory versus empirical evidence. ***Quarterly Journal of Business & Economics***, 35(2): 77-97.

Massari, M., Roncaglio, F., & Zanetti, L. 2008. On the equivalence between the APV and the WACC approach in a growing leveraged firm. ***European Financial Management***, 14(1): 152-162.

Miles, J., & Ezzell, J. 1985. Reformulating tax shield valuation: a note. ***Journal of Finance***, 40(5): 1485-1492.

Modigliani, F., & Miller, M. 1958. The cost of capital, corporation finance and the theory of Investment. ***The American Economic Review***, 48(3): 261-297.

Modigliani, F., & Miller, M. 1963. Corporate income taxes and the cost of capital: a correction. ***The American Economic Review***, 53(3): 433-443.

Mulford, C. 1985. The importance of a market value measurement of debt in leverage ratios: replication and extensions. ***Journal of Accounting Research***, 23(2): 897-906.

Newey, W. K., & West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. ***Econometrica***, 55(3): 703-708.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: comparing approaches. ***Review of Financial Studies***, 22(1): 435-480.

Rubinstein, M. 1973. A mean-variance synthesis of corporate financial theory. ***The Journal of Finance***, 28(1): 167-181.

Taggart, R. 1991. Consistent valuation and cost of capital expressions with corporate and personal taxes. ***Financial Management***, 20(3): 8-20.

Tham, J., & Vélez-Pareja, I. 2004. ***Principles of cash flow valuation*** London: Elsevier Academic Press.

Thompson, S. B. 2011. Simple formulas for standard errors that cluster by both firm and time. ***Journal of Financial Economics***, 99(1): 1-10.

Wang, J., Meric, G., Liu, Z., & Meric, I. 2009. Stock market crashes, firm characteristics, and stock returns. ***Journal of Banking & Finance***, 33(9): 1563-1574.

Table 2-1 Descriptive statistics of the sample data

		Industry Sector												
		1	2	3	4	5	6	7	8	9	10	11	12	Total
Firm-Year observations		3,232	1,541	8,727	3,148	1,771	7,657	1,599	4,360	3,359	4,552	7,821	7,590	55,357
Market Value of Equity	Average	3,286	2,219	1,582	5,781	2,908	2,277	7,692	1,906	1,248	4,619	2,793	2,269	2,773
	StdDev	13,716	6,856	5,136	25,302	7,111	12,259	20,765	3,658	5,140	18,442	12,349	15,736	13,259
	Min	1.26	0.68	0.06	0.78	0.38	0.31	1.34	4.78	0.68	0.91	0.19	0.26	0.06
	Max	176,607	91,168	74,421	468,907	71,147	369,110	237,481	49,189	88,900	263,898	248,791	509,909	509,909
Book Value of Equity	Average	881	1,493	698	2,853	1,023	746	4,301	1,495	525	1,080	1,820	1,038	1,263
	StdDev	2,766	5,160	1,620	9,753	2,152	3,148	12,475	2,428	1,898	4,640	8,557	6,230	5,634
	Min	0.24	0.15	0.03	0.01	0.77	0.03	0.02	0.95	0.04	0.01	0.02	0.00	0.00
	Max	39,619	53,619	21,880	154,396	19,389	58,145	139,911	26,277	38,051	89,953	211,704	164,850	211,704
Debt	Average	674	4,100	528	1,293	816	295	3,335	1,829	420	482	6,507	1,489	1,806
	StdDev	2,354	22,918	1,681	2,762	1,890	1,722	8,412	2,939	1,900	1,926	51,996	16,989	21,105
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	29,122	300,279	35,535	34,322	23,827	35,274	74,991	23,873	33,967	48,662	961,732	523,762	961,732
Debt over Market Equity (5 years moving average)	Average	0.50	0.69	0.56	0.48	0.40	0.19	0.72	1.30	0.63	0.16	1.34	0.72	0.67
	StdDev	0.61	0.93	0.68	0.49	0.36	0.31	0.91	0.69	0.87	0.28	2.90	1.02	1.32
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	2.94	5.74	4.07	2.77	1.78	1.82	6.31	3.77	5.19	1.67	19.21	5.87	19.21
Debt over Book Equity (5 years moving average)	Average	0.66	0.86	0.68	0.87	0.80	0.36	1.38	1.28	0.71	0.41	1.91	0.97	0.91
	StdDev	0.90	1.08	0.79	1.08	1.16	0.58	2.06	0.46	0.75	0.59	4.30	1.29	1.90
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	6.51	7.11	5.22	7.49	8.55	3.66	13.66	3.20	3.73	3.69	29.22	7.93	29.22

Panel B. Excess monthly market returns

		Industry Sector												
Monthly year observations		1	2	3	4	5	6	7	8	9	10	11	12	Total
Firm-Month observations		37,755	18,091	102,401	36,472	20,826	87,779	18,443	51,918	38,723	52,294	90,733	87,882	643,317
Market Excess Returns (%)	Average	1.58	1.48	1.50	1.60	1.52	1.65	1.56	1.25	1.52	1.57	1.21	1.43	1.47
	Std Dev	12.80	13.27	12.84	14.80	12.11	20.50	14.19	6.76	15.30	18.91	13.61	15.72	15.09

Table 2-1 presents the descriptive statistics of the sample of companies used in this study, which comprises listed US firms from 1970 to 2011. Accounting information is obtained from the COMPUSTAT yearly file (Panel A), while market information comes from the CRSP's monthly file (Panel B). Excess market return is the difference between the monthly stock return and one-month Treasury bill return. Market value is calculated as the closing price at the end of the month multiplied by the number of outstanding shares. The BE is stockholders' equity plus deferred taxes minus preferred stock. Debt is defined as the debt held in current liabilities plus long-term debt. Firms are divided following the Fama–French 12-industry-sector specification: consumer non-durables (1), consumer durables (2), manufacturing (3), energy (4), chemicals (5), business equipment (6), telecommunications (7), utilities (8), retail (9), healthcare (10), financial (11), and others (12).

Table 2-2 Summary statistics of the calculated variables

Variable		Mean	Std. Dev.	Min	Max	Observations	
βm_{60}	Overall	1.091	0.66	0.00	4.42	N=	55358
	Between		0.65	0.01	4.42	n=	5885
	Within		0.39	-1.24	3.57	T-bar=	9.41
βu^{MM}	Overall	0.886	0.62	0.00	4.42	N=	55358
	Between		0.64	0.01	4.42	n=	5885
	Within		0.34	-1.44	3.36	T-bar=	9.40663
βu^{ME}	Overall	0.817	0.62	0.00	4.42	N=	55358
	Between		0.64	0.01	4.41	n=	5885
	Within		0.33	-1.51	3.30	T-bar=	9.40663
βl_E^{MM}	Overall	1.180	0.64	0.14	11.18	N=	55358
	Between		0.64	0.01	4.41	n=	5885
	Within		0.33	-1.51	3.30	T-bar=	9.40663
βl_E^{ME}	Overall	1.251	0.88	0.11	15.34	N=	55358
	Between		0.82	0.13	13.83	n=	5885
	Within		0.42	-4.95	11.06	T-bar=	9.40663
βl_{BE}^{MM}	Overall	1.320	0.92	0.14	16.58	N=	55358
	Between		0.93	0.15	15.42	n=	5885
	Within		0.46	-4.85	13.19	T-bar=	9.40663
βl_{BE}^{ME}	Overall	1.453	1.29	0.11	22.94	N=	55358
	Between		1.30	0.13	20.79	n=	5885
	Within		0.63	-7.43	17.36	T-bar=	9.40663
λ_E^{MM}	Overall	1.002	0.60	0.00	7.67	N=	55358
	Between		0.57	0.01	5.20	n=	5885
	Within		0.37	-2.82	5.64	T-bar=	9.40663
λ_E^{ME}	Overall	1.003	0.64	0.00	8.30	N=	55358
	Between		0.62	0.01	6.12	n=	5885
	Within		0.39	-2.95	5.96	T-bar=	9.40663

Table 2-2 shows the summary statistics of the calculated coefficients. The BMKT (*βm*) for each firm is calculated using the individual market returns from the 60 previous months. *βu* is the unlevered beta calculated using equations (2.2) or (2.3). βl is the PLB (equations (2.9) to (2.12)), *βm* is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches.

Table 2-3 Parameters estimates for the regressions among BMKT, PLB and λ

	$\beta l=\beta l_{BE}^{MM}$	$\beta l=\beta l_{BE}^{ME}$	$\beta l=\beta l_{E}^{MM}$	$\beta l=\beta l_{E}^{ME}$
βm	1.07***	1.28***	0.89***	1.04***
	(11.15)	(11.49)	(12.28)	(11.86)
λ_{it}	-1.11***	-0.95***	-1.33***	-1.11***
	(-9.75)	(-10.85)	(-10.41)	(-11.21)
Observations	55,358	55,358	55,358	55,358

Table 2-3 reports the results of the two-dimensional panel regression model as proposed by Cameron et al. (2006), and Petersen (2009) using equation (2.13). Standard errors are calculated by applying the Huber–White sandwich estimators. βl is the PLB (equations (2.9) to (2.12)), βm is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (I) is not tabulated. The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).
* p<0.05, ** p<0.01, *** p<0.001.

Table 2-4 Tests of the difference between the results using the MM and ME models

	Panel A: BMM=PLB
$\beta m = \beta l_{E}^{ME}$	-30.722***
$\beta m = \beta l_{E}^{MM}$	-38.284***
$\beta m = \beta l_{BE}^{ME}$	-73.910***
$\beta m = \beta l_{BE}^{MM}$	-60.523***
	Panel B: MM=ME
$\beta u^{MM} = \beta u^{ME}$	203.131***
$\beta l_{E}^{MM} = \beta l_{E}^{ME}$	-46.947***
$\beta l_{BE}^{MM} = \beta l_{BE}^{ME}$	-107.433***

Table 2-4 presents the results (z-statistics) of the Wilcoxon signed-rank test for paired observations on the pooled sample. Panel A reports the results of the null hypothesis: BMM = PLB. Panel B shows the results of the null hypothesis: $\beta^{MM}=\beta^{ME}$. βu is the unlevered beta calculated using equations (2.2) or (2.3). βl is the PLB. The subscript E indicates the calculation using the market value of equity, and the subscript *BE* specifies the book value of equity. The superscripts *ME* and *MM* correspond to the unleveraged/leveraged process suggested by the *MM* and *ME* method.
 * p<0.05, ** p<0.01, *** p<0.001.

Table 2-5 Parameter estimates for the regressions among BMKT, PLB, and λ excluding the financial and the utilities sectors

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
βm	0.985***	1.143***	0.848***	0.957***
	(15.45)	(15.87)	(17.93)	(17.55)
λ_{it}	-1.153***	-1.340***	-1.019***	-1.163***
	(-14.78)	(-17.99)	(-10.41)	(-18.66)
Observations	43,176	43,176	43,176	43,176

Table 2-5 reports the results of the two-dimensional panel regression model as proposed by Cameron et al. (2006), and Petersen (2009) using equation (2.13). Standard errors are calculated by applying the Huber–White sandwich estimators. In this subsample, we exclude both the utilities and the financial sectors. βl is the PLB (equations (2.9) to (2.12)), βm is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (I) is not tabulated. The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).
* p<0.05, ** p<0.01, *** p<0.001.

Table 2-6 Parameter estimates for the regressions among BMKT, PLB, and λ using subsamples

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
Panel A. Subsample from 1975 to 1990				
βm	1.206***	1.452***	1.216***	1.451***
	(9.2)	(9.14)	(13.15)	(12.93)
λ_{it}	-1.175***	-1.245***	-1.343***	-1.437***
	(-8.20)	(-10.28)	(-8.52)	(-10.55)
Panel B. Subsample from 1991 to 2011				
βm	1.041***	1.248***	0.785***	0.893***
	(9.25)	(9.48)	(10.04)	(10.03)
λ_{it}	-1.102***	-0.843***	-1.326***	-0.970***
	(-8.03)	(-8.68)	(-8.37)	(-8.97)
Observations	18,433	18,433	18,433	18,433

Table 2-6 reports the results of the two-dimensional panel regression model as proposed by Cameron et al. (2006), and Petersen (2009) using equation (2.13). Standard errors are calculated by applying the Huber–White sandwich estimators. Panel A shows the estimates using the subsample from 1975 to 1990, and Panel B presents the estimates of the subsample from 1991 to 2011. *βl* is the PLB (equations (2.2) or (2.3)), *βm* is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (*I*) is not tabulated. The subscript *E* indicates the calculation using the market value of equity, and the subscript *BE* specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME methods. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).

* $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 2-7 Parameter estimates for the regressions among BMKT, PLB, and λ using a 5-year-spaced dataset

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
βm	1.075***	1.277***	0.897***	1.042***
	(6.23)	(6.63)	(6.61)	(6.36)
λ_{it}	-1.136***	-0.968***	-1.341***	-1.127***
	(-6.16)	(-6.43)	(-6.91)	(-6.70)
Observations	11,799	11,799	11,799	11,799

Table 2-7 reports the results of the two-dimensional panel regression model as proposed by Cameron et al. (2006), and Petersen (2009) using equation (2.13). Standard errors are calculated by applying the Huber–White sandwich estimators. We use a subsample with observations from the year 1975 and its multiples (i.e. 1980, 1985, etc.). *βl* is the PLB equation, *βm* is the BMKT, and *λ* is the discrepancy term in the unleveraged/leveraged process. The vector of industrial-sector dummies (*I*) is not tabulated. The subscript *E* indicates the calculation using the market value of debt, and the subscript *BE* specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses)
* p<0.05, ** p<0.01, *** p<0.001.

Appendix 2

Table 2-8 Parameters estimates for the Newey-West regressions among BMKT, PLB, λ and year dummies.

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
βm	1.04***	1.20***	0.90***	0.99***
	(40.97)	(34.96)	(49.92)	(40.95)
λ_{it}	- 1.10***	- 1.27***	- 0.95***	- 1.08***
	(-31.13)	(-28.52)	(-35.29)	(-31.56)
Observations	55,358	55,358	55,358	55,358

Table 2-8 reports the results of the Newey West regressions using equation (2.13). βl is the PLB (equations (2.9) to (2.12)), λ is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (I) is not tabulated. The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).

* p<0.05, ** p<0.01, *** p<0.001.

Table 2-9 Parameters estimates for the fixed-effects regressions among BMKT, PLB, λ and year dummies.

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
βm	0.80***	0.92***	0.68***	0.75***
	(24.50)	(21.96)	(24.42)	(20.64)
λ_{it}	- 0.77***	- 0.89***	- 0.69***	- 0.77***
	(-23.44)	(-21.75)	(-22.65)	(-20.16)
Observations	55,358	55,358	55,358	55,358

Table 2-9 reports the results of the fix effect regressions using equation (13). Standard errors are calculated by applying the Huber–White sandwich estimators. βl is the PLB (equations (2.9) to (2.12)), βm is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (I) is not tabulated. The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).

* p<0.05, ** p<0.01, *** p<0.001.

Table 2-10 Parameters estimates for the Fama-MacBeth regressions among BMKT, PLB and λ.

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
βm	1.35***	1.60***	1.09***	1.26***
	(14.49)	(16.28)	(15.98)	(17.26)
λ_{it}	- 1.38***	- 1.59***	- 1.16***	- 1.32***
	(-14.34)	(-15.54)	(-15.98)	(-17.83)
Observations	55,358	55,358	55,358	55,358

Table 2-10 reports the results of the fix effect regressions using equation (13). Standard errors are calculated by applying the Huber–White sandwich estimators. *βl* is the PLB (equations (2.9) to (2.12)), *βm* is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (I) is not tabulated. The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).

* p<0.05, ** p<0.01, *** p<0.001.

Table 2-11 Parameters estimates for the fixed-effects regressions among BMKT, PLB and λ with Driscoll-Kraay standard errors.

	$\beta l = \beta l_{BE}^{MM}$	$\beta l = \beta l_{BE}^{ME}$	$\beta l = \beta l_{E}^{MM}$	$\beta l = \beta l_{E}^{ME}$
βm	0.83***	0.94***	0.73***	0.80***
	(24.86)	(25.71)	(28.42)	(22.39)
λ_{it}	- 0.82***	- 0.93***	- 0.73***	- 1.32***
	(-17.77)	(-18.67)	(-18.32)	(-16.82)
Observations	55,358	55,358	55,358	55,358

Table 2-11 reports the results of the fix effect regressions using equation (13). Standard errors are calculated by applying Driscoll-Kraay estimators, adjusted by autocorrelation by using the Newey–West correction. *βl* is the PLB (equations (2.9) to (2.12)), *βm* is the BMKT, and λ is the discrepancy term in the unleveraged/leveraged process (equation (2.6)). The vector of industrial-sector dummies (I) is not tabulated. The subscript E indicates the calculation using the market value of equity, and the subscript BE specifies the book value of equity. The superscripts ME and MM correspond to the unleveraged/leveraged process suggested by the MM and ME approaches. The first row of each variable reports the coefficients, and the second row in each panel reports the corresponding t-statistics (in parentheses).
* $p<0.05$, ** $p<0.01$, *** $p<0.001$.

PAPER 3.

Presented at 20th Annual Conference of the Multinational Finance Society (Izmir, Turkey, June 2012).

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Estimating the cost of equity capital for private firms using accounting fundamentals[1]

3.1 Introduction

Estimating the cost of capital and the required rate of return on risky assets is a major concern in the financial sector. Despite all the limitations signalled by the literature[2], the Capital Asset Pricing Model (CAPM) is perhaps the most widely used model for calculating the cost of equity capital (Graham and Harvey, 2001; Levy, 2010). The application of this model requires estimating beta as the systematic risk factor, which is normally achieved by running the regression of stock returns against the market return. However, stock market data is not available for private firms. Even in the case of public firms, there are circumstances under which we may not be able to use market data in order to calculate beta. For instance, when a firm goes public for the first time, a period may last for up to two years during which there is not enough market data with which to run a meaningful regression. In addition, when a public firm goes through significant restructuring, its risk characteristics can change to the extent that using the market beta to calculate the cost of capital may become meaningless.

An approach to overcome the lack of market price data for private firms is to estimate the market risk parameters from the accounting data. According to this method, a firm-based measure of the accounting return is regressed on the changes in the market-wide excess-return index to arrive at an estimate of systematic risk (Beaver *et al.*, 1970).

The role of BACC in systematic risk calculation was largely tested in the seventies and early eighties in the US stock market by establishing its statistical relationship with the CAPM Market Beta (BMKT). These early studies came up with a general (although not unanimous) conclusion that BACC is significantly correlated with BMKT.

[1] Sarmiento-Sabogal, Julio and Sadeghi, Mehdi. Candidate contribution: data collection, literature review, research design and analysis of results, which account for about 90% of the paper. The co-author have contributed with his comments and corrections of the paper.

[2] Johnstone (2013) offers an up-to-date debate on the validity of CAPM.

However, most recent studies show contradictory evidence as to these findings. For example, Cohen *et al.* (2009) and Nekrasov and Shroff (2009) apply BACC as a substitute method for BMKT, while Campbell *et al.* (2010) find BACC to be a weak predictor of BMKT. Furthermore, the majority of previous studies, which have discussed their reasons for choosing a specific accounting measure of return, do not investigate which method has a superior empirical performance (if this superiority actually exists)[3]. Finally, the heavily researched area on the relationship between accounting fundamentals and stock price dynamics makes little reference to the contemporaneous and specific relationship between BACC and BMKT. The absence of empirical studies in this sense may also challenge the validity of the commonly used BACC proxy measure by practitioners in calculating the cost of equity capital for unlisted companies.

The aim of the current study is to fill this research gap and test the performance of BACC as a proxy measure of systematic risk using a panel data approach. Unlike previous studies, panel data provides us with the opportunity to examine this relationship more comprehensively, across both different time periods and different companies. We also conducted a longitudinal analysis to capture changes in the link between BMKT and BACC over time more efficiently.

The study of the BACC–BMKT relationship is conducted in four steps: First, we compute BMKT and eight versions of BACC using three different time windows of 60 (5), 120 (10), and 180 (15) months (years) for BMKT (BACC), composed of 14,897 firm-year observations of US listed firms. Second, we run a univariate regression between BMKT and each version of BACC to determine whether all BACC estimates are linked statistically with BMKT at the conventional levels. Third, we attempt to find possible explanations for a large group of negative BACC coefficients that we found in our estimations. Finally, we measure the statistical significance of the difference among BMKT and its accounting counterparts.

Our results indicate that although BACC is strongly correlated with BMKT, its application in computing the discount rate for small firms leads to spurious, negative BACC coefficients. This is an indication of the shortcomings of using BACC when

[3] The recent paper from Barton *et al.* (2010) explores the value relevance of a broad range of income statement figures. The authors argue that operational measures in the middle of the financial statement better explain stock returns.

calculating the cost of capital for small firms. However, it alerts researchers to the fact that although data transformations, such as logarithmic smoothing or winsorization of the values under zero used in previous studies may eliminate the spurious negativity of BACC coefficients, they lead to data-selection bias. Finally, we measure the statistical significance of the difference among BMKT and its accounting counterparts. The results reveal that BACC coefficients are 20%–50% ($P < 0.05$) larger than BMKT.

The remainder of this paper is as follows: In Section 3.2, we present a summary of the literature regarding accounting betas. In Section 3.3, we describe our dataset and methodology. Section 3.4 is devoted to explore the relationship between BACC and BMTK.. In section 3.5, we examine the possible reasons of a persistent set of negative BACC estimates. In section 3.6, we measure the differences between BACC and BMKT and Section 3.7 concludes.

3.2 Literature Review

The development of the CAPM in the mid-sixties was followed by an explosion of studies that explored the link between the systematic risk and accounting variables, both from the theoretical and empirical perspectives. In the theoretical sense, Ohlson (1979) study asserts that BACC is theoretically related to BMKT, assuming that accounting variables follow a stochastic process. Bowman (1979) establishes the theoretical relationship between BACC and BMKT as $BMKT = (Sm_i/S_i)BACC$, where Sm_i represents the sum of the total market value of equity when all firms in the market are unlevered, and S_i is the market value of the specific asset. This theoretical approximation seems to have an issue, in that all accounting betas are an indirect function of the size of their stock market; thus, the resulting estimate of BACC is a small number (Bowman, 1980).

In the empirical sense, the seminal paper by Beaver et al. (1970) tests the relationship between BMKT and BACC, among other accounting-based measures of risk. The empirical results of their findings suggest that accounting and market betas have a statistically significant relationship. Although most of early studies[4] support Beaver et al. (1970) conclusions, (Gonedes, 1973a, 1973b, 1975) finds contradicting

[4] See, for example, Hill and Stone (1980) and Lev and Sunder (1979).

results, attributing the significance of previous findings to possible spurious correlations. Indeed, the large debate over Gonedes' work might have arisen from the relatively weak relationship between BACC and BMKT, to the extent that a minor change either in the studied period or in the regression technique could have caused the correlation to appear or disappear.

A paper by Ismail and Moon (1989) explores the explanatory power of cash flow as a proxy for BMKT. They argue that cash flow-related measures provide additional information relative to the accrual earnings. In a more recent study, Cohen et al. (2009) directly use BACC as a substitute for BMKT, and argue that the latter may generate overoptimistic results when testing the CAPM. The authors of these papers find that BACC is able to explain long-horizon returns. In contrast, Campbell et al. (2010) argue that this measure is a weak predictor of future BMKT[5].

To sum up, most authors agree that: First, there is a significant relationship between BACC and BMKT, and second, this relationship explains only a fraction of the systematic risk. The latter conclusion plays a pivotal role in the application of BACC as a substitute for BMKT. This is due to the fact that if the link is not strong enough, then the correlation may be useful for explanatory purposes, but it cannot be used for substitution purposes.

3.3 Dataset and Methodology

The dataset is composed of 14 897 firm-year observations of US listed firms whose annual accounting information is available in COMPUSTAT. Market capitalization and monthly returns were collected from the Center of Research of Security Prices (CRSP). The studied period includes the years from 1972 to 2011. Each firm should have at least one observation for all of the calculated variables to be included in the sample. We exclude firms with a fiscal year end other than December, as well as companies with negative equity.

[5] Other studies have tangentially tested BACC. For example, Baginski and Wahlen (2003) conclude that BACC and BMKT have a statistically significant but small relationship. These findings are confirmed by Nekrasov and Shroff (2009).

3.3.1 Methodology

Our methodology is mainly adopted from Ismail and Moon (1989), and is applied in four steps: First, we compute the monthly BMKT using the standard model. Second, we calculate eight versions of the annual BACC. Third, we match two samples by dropping every month except December in each year[6]. Finally, we run the panel regressions between BMKT and BACC. We winsorize the collected firm's Monthly Return *(R_{it})* from the CRSP within the monthly 1% and 99% percentiles. This procedure avoids any statistical leverage caused by extreme observations. The firm's excess return is R_{it} minus the one-month T-bill return. The market excess return of a value-weighted portfolio is obtained from Keneth French's[7] webpage. We compute three versions of BMKT by using the sixty ($BMKT_{60}$), one hundred and twenty ($BMKT_{120}$), and one hundred and eighty ($BMKT_{180}$) previous months.

Similar to Campbell and Mei (1993a), we define BACC as the regression between the yearly variations of the Accounting Return (*RA*) and the market-weighted portfolio, as follows:

$$BACC_{it} = \frac{Cov\left(dRA_{it}, dRA_M\right)}{Var\left(dRA_M\right)} \tag{3.1}$$

where *d* indicates lagged variation. The accounting ratio of the firm *i* at period *t* is computed as $RA_{it} = log(1 + RA_t) - log\ (1\ +\ RA_{t-1})$. The proxy for the accounting return variation of the market dRA_M is computed from an asset-value-weighted portfolio composed by the firms in the sample, rebalanced on a yearly basis. We compute BACC using windows of 5, 10, and 15 previous years. Hence, we obtain three BACC matrixes starting in 1986 and finishing in 2011. Note that information from 1972 to 1986 is required to calculate the first beta estimate over a window of 15 years.

We estimate the following proxies for *RA*[8, 9]:

- *EBITDA* to Assets (*EBTA*)
- *EBIT* to Assets (*OITA*)

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[6] Our findings do not essentially change by using data from yearly averages or June instead of December.

[7] We use the *Rm-Rf* component of the Fama–French factors, as updated by Keneth French on his web page http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[8] All balance sheet data (denominators of the relationship) have been taken from the beginning of the period.

[9] Appendix 1 contains the detailed information of the variable calculations.

- Net Income to Assets (*ROA*)
- *EBITDA* to Equity (*EBCE*)
- *EBIT* to Equity (*OICE*)
- Net Income to Equity (*ROE*)
- Operating Cash Flow to Assets (*CFTA*)
- Operating Cash Flow to Equity (*CFCE*)

We get an unbalanced panel with nine betas for each year-firm: the BMKT is calculated on a monthly basis with information from the 60, 120, and 180 previous months, and eight versions of BACC are computed from the 5, 10, and 15 preceding years.

Table 3-1 presents the summary statistics of the calculated coefficients. Panel A presents the calculations based on 5 years for BACC and 60 months for BMKT. Panel B shows the calculations based on 10 years and 120 months, and Panel C reports the estimates computed from 15 years and 180 months. The three last rows of each panel correspond to percentiles 25, 50, and 75, respectively. We calculate and analyse the information in Panel A, while understanding that the relatively few observations that we used (5 points) may lead us to a spurious analysis.

The findings in Table 3-1 show that BMKT estimates ($BMKT_{60}$ = 0.88, $BMKT_{120}$ = 0.85, and $BMKT_{180}$ = 0.88) tend to be higher than all versions of BACC, which fluctuate from 0.15 ($FCTA_5$ and $FCCE_5$) to 0.90 (ROA_{10}). Previous studies do not provide a clear explanation for this behaviour, because most of them use balanced panel data with an equally weighted market portfolio that ensures that the BMKT average is equal to unity[10]. There are a number of possible explanations for our finding: i) the smaller coefficients might be an indication of a weaker relationship between the accounting return and the market returns; ii) these near-zero coefficients may indicate that our selected proxy for the market return is less efficient than the BMKT market excess return (Roll and Ross, 1994)[11]; and iii) Cohen *et al.* (2009) assert that BMKT might

[10] See, for example, Beaver *et al.* (1970), Beaver and Manegold (1975), and Ismail and Moon (1989).

[11] However, the results persist even when we use the same market excess return that we employ to compute BMKT (not tabulated but available from the authors).

artificially increase the slope of the estimated equations for small firms, whereas BACC is unlikely to cause this problem.

The comparison of the means and the medians (p50 row) in Table 3-1 indicates that with the exception of *FCTA* (i.e. Mean of $FCTA_{15}$ = 0.41; Median of $FCTA_{180}$ = 0.44), all of the estimated variables are positively skewed (i.e. Mean of ROA_{15} = 0.88; Median of ROA_{15} = 0.57). As expected, the standard deviation of all of the estimates narrows with increasing observations. The standard deviation for the BACC estimates is higher than the same statistic for BMKT. This could be due to value-irrelevant noise in the fundamental return measures, which is consistent with the findings of Lev (1989) and Collins *et al.* (1994).

The large number of negative betas (25%) in the first quartile reported in Table 3-1 (p25 row) seems counter-intuitive. Section 3.5 is devoted to further discussion of this issue.

3.4 The relationship between BACC and BMKT

We run univariate regressions between BMKT and each version of BACC using the following model:

$$BMKT_m^{it} = \alpha_1 + \alpha_2 BACC_n^{is} + \varepsilon \qquad (3.2)$$

where subscript *m* represents the number of previous months and the corresponding *n* years used to calculate the coefficient. Superscripts *i* and *t (s)* denote the firm and month (year), respectively. Table 3-2 reports the results of the two-dimensional longitudinal regression as proposed by Cameron *et al.* (2006) and Petersen (2009) fitting model (3.2). The standard errors are computed based on Huber–White sandwich estimators[12] to account for heteroskedasticity. We run the regression three times using different time windows: 60 (5), 120 (10), and 180 (15) months (years) for BMKT (BACC). It is hypothesised that BACC is directly correlated with BMKT. The estimated coefficients should approach unity, as the rate of change for a "perfect" proxy must be the same as the original measure. The outputs have the expected positive sign, and range from 0.015 ($FCTA_{15}$) to 0.082 ($EBTA_{15}$). However, they are far from the expected value of one. In fact, none of the maximum values of the coefficient intervals at the 95%

[12] The advantages of this estimation is pointed out by Gow *et al.* (2010); Petersen (2009), and (Thompson, 2011), when rebalanced on a yearly basis.

significance level (third row of each regression) is higher than 0.10. This may indicate that BACC is related to BMKT, but is not a perfect proxy for it.

The *t*-statistics in Table 3-2 (the second row of each estimate) show that the figures based on assets instead of equity seem to have a stronger link with BMKT. For example, ROA_{15} (t = 8.68) is larger than ROE_{15} (t = 7.19), and $OITA_{10}$ (t = 8.19) is larger than $OICE_{10}$ (t = 7.65). Although this finding is consistent with Beaver and Manegold (1975), it is not aligned with the theory. We presume that BACC estimates determined from equity are more allied with BMKT than proxies based on assets, since the latter are computed from (market) equity. Ball *et al.* (2009) argue that *ROE* has a heavier negative tail than *ROA,* and that this produces a weaker relationship between accounting fundamentals and stock returns.

Further findings in Table 3-2 indicate that estimates based on cash flow figures have the weakest relationship with BMKT. This coefficient becomes significant only in the longest time window, contradicting Ismail and Moon (1989) findings, who showed that cash-related betas have a stronger link with BMKT than earnings-based betas. However, our results are consistent with Dechow (1994), who argues that accruals are more reliable measures of firm performance.

The results in Table 3-2 also suggest that the relationship between BACC and BMKT is robust to a variety of accounting return specifications and time windows. This association increases monotonically with the expansion of the time window, providing a plausible explanation for the common agreement in the literature on the link between these measures[13]. We focus on this issue in more detail in Section 3.6.

3.5 The informational content of negative BACC estimates

This section addresses the issue of the prevailing negative relationship between BACC and BMKT discussed in Table 3-1. There are two possible (exclusive) explanations for this issue: i) the outputs may be the result of a risk-irrelevant noise that is not excluded from our regressions; and ii) the negative coefficients may be a sign of a genuine inverse relationship between BACC and BMKT. Unfortunately, earlier studies do not provide any information on the negative sign of beta in their estimates, and most

[13] Despite different definitions of the BACC that some of these studies have used.

recent studies have avoided this problem by using a logarithmic function (Schlueter and Sievers, 2011) or by winsorizing the values of beta that are smaller than zero (Nekrasov and Shroff, 2009).

We run a multivariate logit model to examine whether the negative estimates discussed above are attributed to some firm characteristics:

$$NBACC_{it} = \alpha_1 + \alpha_2 SMALL_{it} + \alpha_3 VALUE_{it} + \alpha_4 NEGATIVE_{it} + \varepsilon_{it} \qquad (3.3)$$

We start to apply this model by dividing the BACC estimates into positive and negative groups in order to determine whether some firm characteristics may explain the negative property of BACC coefficients. The dependent variable, *NBACC*, which represents the negative group of data, is set to one (zero) if BACC is less (more) than zero. The independent variable, *SMALL*, which represents the size, is set to one if the firm assets are in the lowest 20% of the yearly percentile[14]. The *VALUE*, which is the book-to-market capitalization, is set to one for those firms whose ratio falls in the lowest quintile each year. *NEGATIVE*, representing a negative $BMKT_{180}$, is set to one when this variable is negative. All these dummy variables are initially set to zero. Both *SMALL* and *VALUE* isolate the effect of the riskiest portfolio in the Fama and French (1993) model specification. Including *NEGATIVE* in the model allows us to examine whether the negative coefficients arise from using BACC, or from using BMKT as a measure of systematic risk[15].

Table 3-3 reports the output for each studied BACC version for estimates based on 180 months for BMKT and 15 years for BACC. The standard errors are clustered by year and firm (Petersen, 2009). The estimates propose that *SMALL* is statistically positively correlated with *NBACC* in all studied BACC versions with *t*-statistics varying from 2.04 ($EBTA_{15}$) to 3.06 (ROE_{15}), while *VALUE* is significant only for the $EBTA_{15}$ ratio ($p < 1\%$), and *NEGATIVE* is significant in two out of eight BACC ratios: $EBTA_{15}$ ($p < 5\%$) and *OITA* ($p < 5\%$). These outcomes evidence that *NBACC* seems to have a structural link with the size of the firms. Specifically, BACC may produce systematically negative estimates for small firms. The link between *NBACC* ($EBTA_{15}$ and $OITA_{15}$) and *NEGATIVE* suggests that BACC might amplify the shortcomings in

[14] The asset mean of *SMALL* firms is US$16.4 million.

[15] The results of an alternative specification of model (3.3) using the book-to-market and size values instead of the dummies are presented in Table 3-6. Although the results are similar to those obtained here, the relationship between NBETA and firm characteristics become weaker for some BACC versions.

the risk assessment of the CAPM in the sense that (other characteristics aside) small firms should have larger discount rates than larger firms should. Hence, the elimination of these negative coefficients to test the performance of BACC may lead to a selection bias if the results are generalized.

The conclusion from Table 3-3 is that the BACC estimates do not work well for small companies, and that using this estimate as a proxy for calculating the discount rate for such firms may lead to an underestimation or even a negative hurdle rate. A study by Fama and French (2002) identifies the source of this problem in the CAPM model, asserting that stock returns capture information beyond the mean-variance framework, where CAPM is not capable of explaining the difference between small and large firms. Zhang (2006) also asserts that small firms tend to have more information uncertainty and are more prone to the mispricing issue in CAPM.

3.6 Measuring the differences between BACC and BMKT

In this section, we investigate whether the BACC is a good proxy variable for BMKT by measuring the differences between their estimates. We create a subsample with all non-negative estimated coefficients[16] and perform Somers' D test (Somers, 1962) for paired observations on the pooled sample[17].

This test computes the ranking concordant (*C*) and disconcordant (*D*) pairs scaled by the total number of possible combinations plus the number of tied pairs (*T*). Thus,

$$Somers'D = \frac{C - D}{N!/2!(N-2)+T} \tag{3.4}$$

This allows us to calculate the statistical significance of the asymmetrical difference[18] between BACC and BMKT, as well as the confidence interval (*CI*) of this deviation. The *CI* parameter is pivotal in our study to find whether BACC tends to over-estimate or under-estimate BMKT. Alternative tests, such as the Wilcoxon test, do not provide *CI* estimates.

[16] The summary statistics of this subsample are presented in Appendix 2.

[17] Newson (2006) gives a detailed explanation about the implementation of this test.

[18] The descriptive statistics in Table 1 indicate that BACC estimates are positively skewed.

Panel A in Table 3-4 presents the results of all paired combinations in our subsample using estimates based on 180 months for BMKT and 15 years for BACC. On each combination, we test the null hypothesis $K - R = 0$, where K is the column variable and R represents the row variable. We report the Somers' D estimate (most likely value) in the first row and the confidence in the second and third rows. For example, the interception between the first column ($BMKT_{180}$) and the first row (ROE_{15}) shows the outcome of the pairwise test $BMKT_{180} - ROE_{15} = 0$. The results indicate that systematic risk is over-estimated (negative sign) by approximately 25.90% when $BMKT_{180}$ is compared with ROE_{15} (CI : 28.33%–23.44%, $p < 0.05$). Evidence from the first column reveals that there is a significant difference between the BMKT and BACC estimates. Therefore, the application of the latter to compute the cost of equity capital may imply an over-estimation of the systematic risk in the range from 19.62% ($OICE_{15}$) to 49.49% ($OITA_{15}$).

A further examination of Table 3-4 shows that the magnitude of the difference between BACC and BMKT seems to be driven by the balance sheet figures, since proxies that use assets in the ratio denominator give similar large Somers' D coefficients ($OITA_{15}$ = −47.67%, $EBTA_{15}$ = −41.01%, ROA_{15} = −46.01%, $FCTA_{15}$ = −43.30%), while the estimates computed from equity have smaller results ($OICE_{15}$ = −22.19%, $EBCE_{15}$ = −22.0%, ROE_{15} = −25.90%, $FCCE_{15}$ = −25.04%). The differences between analogous measures in the numerator, by using different bases in the denominator, are always significant at the 1% level (i.e. $OITA_{15} > OICE_{15}$ and $ROA_{15} > ROE_{15}$). When comparing the performance[19] of the earning figures, there are slightly better results when using operational-based numbers. Although this finding is consistent with the study from Barton *et al.* (2010), the statistical significance among the operational measures of return is weak.

Panel B in Table 3-4 reports the output of an alternative rank test proposed by Nekrasov and Shroff (2009). The yearly ranking errors (E_t) are computed using the following equation:

$$E_t = ABS\left[(\omega_t\left(BMKT\right) - \mu_t(BACC)\right] / N_t \quad (3.5)$$

where ω_t is the ranking of this firm each year (t) sorted by BMKT, μ_t is the ranking sorted by BACC, and N_t is the yearly number of firms in the sample. While the Somers'

[19] The use of proxy measures presumes that the least distance there is the better.

D test evaluates all possible pairwise cases, the Nekrasov and Shroff (2009) test measures the errors based on the total ranking each year. The results in Panel B suggest that the smaller errors are produced by *OICE* (20.40%) and *EBCE* (21.05%), while the larger errors are given by *FCTA* (36.13%) and *ROA* (36.11%). The information obtained in Panel B confirms that discrepancies among errors are related to the selection of common equity or total assets in the denominator of BACC, as well as to the superior performance of ratios using *EBIT* or *EBITDA* when they are compared with results based on net income or cash flow.

The overall findings allow us to make some inferences about the possible consequences of using BACC as a proxy to measure the cost of capital of unlisted targets. First, using BACC instead of BMKT to compute the cost of equity capital is not misleading due to the strong correlation between the two. This is in line with previous authors' findings (see, for example, Cohen *et al.* (2003); Nekrasov and Shroff (2009)). Second, the application of BACC to small firms is likely to generate unwarranted outcomes and negative spurious estimates. Third, the usage of BACC implies an over-estimation of the systematic risk that may generate an undervaluation of the private equities. Finally, this over-estimation might be reduced, but not eliminated by using measures based on operational income (such us *EBIT* or *EBITDA*) scaled by the book value of equity.

3.7 Conclusions

CAPM is perhaps the most widely used model to calculate the cost of equity capital. However, the absence of necessary market information for private equities to calculate the Market Beta (BMKT) restricts the application of this model to the listed firms. Finance literature suggests the use of Accounting Betas (BACC) as a proxy measure for the CAPM Market Beta (BMKT) when market information is not available. The current study examines the relationship between BACC and BMKT and yields to fourth conclusions.

First, we found a pervasive link between BACC–BMKT for the eight different versions of BACC estimates. Second, we find that the link between BACC–BMKT measures is almost insensitive to the time window used to compute the coefficients. We further provide evidence that measures based on accruals have a stronger relationship than those measures that use cash flows. This finding supports the common use of *ROE*-based measures in the stock return literature (i.e. Cohen *et al.* (2003), Nekrasov and Shroff (2009), and Cohen *et al.* (2009), among others), but contradicts the conclusions reached by Ismail and Moon (1989). Third, the design of our research[20] resulted in the detection of a large number of negative BACC estimates that are structurally linked to the size of the firms. This led to further examination of this problem. Our findings indicate that BACC may amplify the shortcomings of the risk assessment of small firms. Fourth, the finance literature suggests the use of BACC as proxy method based on regression analysis because of its well-known strong correlation with BMKT (i.e. Baginski and Wahlen (2003), Brimble and Hodgson (2007), Nekrasov and Shroff (2009), among others). However, the magnitude of the error for this substitution is largely unknown. We apply the Somers' D test as a nonparametric measure to quantify this error. The output suggests that using any version of BACC tends to over-estimate BMKT in a range of 20%–50% ($p < 0.05$). The differences among the BACC versions seem to be driven by the selection of the balance sheet figure for the denominator. Ratio estimates based on the assets almost double the over-estimation error compared to those using equity. At the same time, operating earnings are slightly more aligned with BMKT. Therefore, ratios such as *EBITDA* to Equity or *EBIT* to Equity (the *CI* of the difference being 22%–24%, $p < 0.05$) may be used to avoid some of the over-penalization of systematic risk.

Overall, our results indicate that although BACC is strongly correlated with BMKT, its application in computing the discount rate for small firms may lead to spurious negative results. When BACC is used as proxy measure of BMKT, the systematic risk tends to be over-valuated. This difference may be lessened (but not eliminated) by using measures based on operational earnings and on equity rather than assets.

[20] These negative estimates might arise due to a combination of three factors: 1) the inclusion of small firms in the sample; 2) our estimations, which are based on firm-level instead of portfolio aggregation; and 3) the avoidance of sensorization of these estimates, either by using logarithmic models, or by directly winsorizing values below zero.

3.8 References

Baginski, S. P., & Wahlen, J. M. 2003. Residual income risk, intrinsic values, and share prices. ***The Accounting Review***, 78(1): 327-351.

Ball, R., Sadka, G., & Sadka, R. 2009. Aggregate earnings and asset prices. ***Journal of Accounting Research***, 47(5): 1097-1133.

Barton, J., Hansen, T. B., & Pownall, G. 2010. Which performance measures do investors around the world value the most and why? ***The Accounting Review***, 85(3): 753-789.

Beaver, W., Kettler, P., & Scholes, M. 1970. The association between market determined and accounting determined risk measures. ***The Accounting Review***, 45(4): 654-682.

Beaver, W., & Manegold, J. 1975. The association between market-determined and accounting-determined measures of systematic risk: some further evidence. ***The Journal of Financial and Quantitative Analysis***, 10(2): 231-284.

Bowman, R. 1979. The theoretical relationship between systematic risk and financial (accounting) variables. ***The Journal of Finance***, 34(3): 617-630.

Bowman, R. 1980. The importance of a market-value measurement of debt in assessing leverage. ***Journal of Accounting Research***, 18(1): 242-254.

Brimble, M., & Hodgson, A. 2007. Assessing the risk relevance of accounting variables in diverse economic conditions. ***Managerial Finance***, 33(8): 553-573.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. 2006. Robust Inference with Multi-way Clustering. ***National Bureau of Economic Research Technical Working Paper Series***, No. 327.

Campbell, J., & Mei, J. 1993. Where do betas come from? Asset price dynamics and the sources of systematic risk. ***Review of Financial Studies***, 6(3): 567-592.

Campbell, J., Polk, C., & Vuolteenaho, T. 2010. Growth or glamour? fundamentals and systematic risk in stock returns. ***Review of Financial Studies***, 23(1): 305-344.

Cohen, R., Polk, C., & Vuolteenaho, T. 2003. The value spread. ***The Journal of Finance***, 58(2): 609-642.

Cohen, R., Polk, C., & Vuolteenaho, T. 2009. The price is (almost) right. ***Journal of Finance***, 64(6): 2739-2782.

Collins, D. W., Kothari, S. P., Shanken, J., & Sloan, R. G. 1994. Lack of timeliness and noise as explanations for the low contemporaneuos return-earnings association. ***Journal of Accounting and Economics***, 18(3): 289-324.

Daniel, K., & Titman, S. 2006. Market reactions to Tangible and intangible information. ***The Journal of Finance***, 61(4): 1605-1643.

Dechow, P. M. 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. ***Journal of Accounting and Economics***, 18(1): 3-42.

Fama, E. F., & French, K. R. 1993. Common risk factors in the returns on stocks and bonds. ***Journal of Financial Economics***, 33(1): 3-56.

Fama, E. F., & French, K. R. 2002. Testing Trade-Off and Pecking Order Predictions about Dividends and Debt. ***The Review of Financial Studies***, 15(1): 1-33.

Gonedes, N. J. 1973a. Evidence on the information content of accounting numbers: Accounting-based and market-based estimates of systematic risk. ***The Journal of Financial and Quantitative Analysis***, 8(3): 407-443.

Gonedes, N. J. 1973b. Properties of accounting numbers: Models and tests. ***Journal of Accounting Research***, 11(2): 212-237.

Gonedes, N. J. 1975. A note on accounting-based and market-based estimates of systematic risk. ***The Journal of Financial and Quantitative Analysis***, 10(2): 355-365.

Gow, I., Ormazabal, G., & Taylor, D. 2010. Correcting for cross-sectional and time-series dependence in accounting research. ***Accounting Review***, 85(2): 483-512.

Graham, J. R., & Harvey, C. R. 2001. The theory and practice of corporate finance: evidence from the field. ***Journal of Financial Economics***, 60(2-3): 187-243.

Hill, N. C., & Stone, B. K. 1980. Accounting betas, systematic operating risk, and financial leverage: A risk-composition approach to the Ddeterminants of systematic risk. ***Journal of Financial & Quantitative Analysis***, 15(3): 595-637.

Ismail, B. E., & Moon, K. K. 1989. On the association of cash flow variables with market risk: Further evidence. ***The Accounting Review***, 64(1): 125-136.

Johnstone, D. J. 2013. The CAPM debate and the logic and philosophy of finance. ***Abacus***, 49: 1-6.

Lev, B. 1989. On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research. ***Journal of Accounting Research***, 27: 153-192.

Lev, B., & Sunder, S. 1979. Methodological issues in the use of financial ratios. ***Journal of Accounting and Economics***, 1(3): 187-210.

Levy, H. 2010. The CAPM is alive and well: A review and synthesis. ***European Financial Management***, 16(1): 43-71.

Nekrasov, A., & Shroff, P. K. 2009. Fundamentals-based risk measurement in valuation. ***Accounting Review***, 84(6): 1983-2011.

Newson, R. 2006. Confidence intervals for rank statistics: Somers' D and extensions. ***Stata Journal***, 6(3): 309-334.

Ogneva, M. 2012. Accrual Quality, Realized Returns, and Expected Returns: The Importance of Controlling for Cash Flow Shocks. ***The Accounting Review***, 87(4): 1415-1444.

Ohlson, J. A. 1979. Risk, Return, Security-Valuation and the Stochastic Behavior of Accounting Numbers. ***The Journal of Financial and Quantitative Analysis***, 14(2): 317-336.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: comparing approaches. ***Review of Financial Studies***, 22(1): 435-480.

Roll, R., & Ross, S. A. 1994. On the cross-sectional relation between expected returns and betas. ***The Journal of Finance***, 49(1): 101-121.

Schlueter, T., & Sievers, S. 2011. Determinants of market beta: the impacts of firm-specific accounting figures and market conditions. ***Review of Quantitative Finance and Accounting***: 1-36.

Somers, R. H. 1962. A new asymmetric measure of association for ordinal variables. ***American Sociological Review***, 27(6): 799-811.

Thompson, S. B. 2011. Simple formulas for standard errors that cluster by both firm and time. ***Journal of Financial Economics***, 99(1): 1-10.

Zhang, X. 2006. Information uncertainty and stock returns. ***The Journal of Finance***, 61(1): 105-137.

Table 3-1. Summary statistics of the calculated betas

Panel A. Summary statistics of the calculated variables using 5 previous years and the previous 60 months

Stats	BMKT	ROE	ROA	EBTA	EBCE	OITA	OICE	FCTA	FCCE
N	14,897	14,897	14,897	14,897	14,897	14,897	14,897	14,897	14,897
Mean	0.88	0.48	0.78	0.63	0.32	0.68	0.36	0.15	0.15
Std. Dev.	0.54	1.89	2.40	2.34	1.78	2.39	1.68	3.19	2.24
p25	0.50	-0.27	-0.36	-0.52	-0.43	-0.50	-0.36	-2.09	-0.87
p50	0.84	0.20	0.49	0.46	0.19	0.51	0.21	0.19	0.07
p75	1.18	1.16	2.14	1.92	1.01	2.04	0.98	2.47	1.17

Panel B. Summary statistics of the calculated variables using 10 previous years and the previous 120 months

Stats	BMKT	ROE	ROA	EBTA	EBCE	OITA	OICE	FCTA	FCCE
N	14,897	14,897	14,897	14,897	14,897	14,897	14,897	14,897	14,897
Mean	0.85	0.56	0.90	0.75	0.47	0.83	0.50	0.29	0.25
Std. Dev.	0.45	1.46	1.87	1.71	1.38	1.81	1.33	2.48	1.73
p25	0.51	-0.13	-0.10	-0.19	-0.23	-0.17	-0.18	-1.05	-0.54
p50	0.84	0.22	0.54	0.49	0.26	0.56	0.27	0.31	0.18
p75	1.13	1.04	1.84	1.58	1.01	1.75	1.03	1.69	1.00

Panel C. Summary statistics of the calculated variables using 15 previous years and the previous 180 months

Stats	BMKT	ROE	ROA	EBTA	EBCE	OITA	OICE	FCTA	FCCE
N	14,897	14,897	14,897	14,897	14,897	14,897	14,897	14,897	14,897
Mean	0.88	0.51	0.88	0.76	0.49	0.85	0.53	0.41	0.36
Std. Dev.	0.41	1.27	1.62	1.52	1.24	1.64	1.20	2.09	1.49
p25	0.56	-0.10	-0.04	-0.10	-0.17	-0.09	-0.14	-0.56	-0.35
p50	0.88	0.21	0.57	0.52	0.29	0.58	0.32	0.44	0.29
p75	1.14	0.92	1.70	1.49	1.00	1.66	1.02	1.53	1.02

Table 3-1 shows the summary statistics of the calculated coefficients. Panel A presents the calculations based on the 5 years for accounting variables and 60 months for the Market Beta (BMKT). Panel B shows the calculations based on 10 years and 120 months, and Panel C reports on 15 years and 180 months. The three last rows of each panel correspond to percentiles 25, 50, and 75, respectively. *EBTA* is *EBITDA* to Total Assets. *ROA* is *EBIT* to Total Assets. *NITA* is Net Income to Total Assets. *EBCE* is *EBITDA* to Equity. *OICE* is *EBIT* to Equity. *ROE* is Net Income to Equity. *FCTA* is Operating Cash Flow to Total Assets and *FCCE* is Operating Cash Flow to Equity.

Table 3-2. Parameter estimates of regressions of BACC on BMKT.

	ROE	ROA	EBTA	EBCE	OITA	OICE	FCTA	CFCE
$BMKT_{60}$	0.045***	0.039***	0.039***	0.027***	0.039***	0.034***	0.003	0.002
	(4.86)	(4.81)	(5.50)	(4.20)	(5.68)	(4.71)	(0.73)	(0.35)
	[0.03-0.06]	[0.02-0.06]	[0.03-0.05]	[0.01-0.04]	[0.03-0.05]	[0.02-0.05]	[-0.00-0.01]	[-0.01-0.01]
$BMKT_{120}$	0.070***	0.067***	0.072***	0.060***	0.067***	0.0682***	0.007	0.006
	(7.47)	(8.03)	(8.18)	(7.02)	(8.10)	(7.65)	(1.61)	(1.14)
	[0.05-0.09]	[0.05-0.08]	[0.05-0.09]	[0.04-0.08]	[0.05-0.08]	[0.05-0.09]	[0.00-0.02]	[0.00-0.02]
$BMKT_{180}$	0.071***	0.074***	0.082***	0.074***	0.075***	0.082***	0.015***	0.016***
	(7.19)	(8.69)	(9.67)	(7.97)	(9.55)	(8.21)	(3.62)	(2.65)
	[0.05-0.09]	[0.06-0.09]	[0.06-0.10]	[0.06-0.09]	[0.06-0.09]	[0.06-0.10]	[0.01-0.02]	[0.00-0.03]

Table 3-2 reports the results of the two-dimensional panel regression model as proposed by Cameron et al. (2006), and Petersen (2009). Model (2) is fitted by running univariate regressions between the Market Beta (BMKT) and each one of the eight studied definitions of Accounting Betas (BACCs) using three different time windows of 60 (5), 120 (10), and 180 (15) months (years) for BMKT (BACC). Standard errors are calculated by applying the Huber–White sandwich estimators. *EBTA* is Earnings Before Interests, Taxes, Depreciations and Amortizations (*EBITDA)* to Assets. *OITA* is *EBTA,* which is Earnings Before Interests, Taxes *(EBIT*), to Assets. *NITA* is Net Income to Assets. *FCTA* is Operational Cash Flow to Assets. *EBCE* is *EBITDA* to Equity. *OICE* is *EBIT* to Equity. *NICE* is Net Income to Equity. *CFCE* is Operational Cash Flow to Equity. The first row in the table reports the coefficients and the second row reports the corresponding *t*-statistics (in parentheses).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3-3. Logit regression estimates of negative BACCs on firm characteristics.

	ROE	ROA	EBTA	EBCE	OITA	OICE	FCTA	FCCE
SMALL	0.32**	0.45***	0.23*	0.32**	0.24*	0.3**	0.36***	0.27*
	(3.06)	(3.99)	(2.04)	(2.70)	(2.13)	(2.68)	(3.50)	(2.46)
VALUE	-0.04	0.03	0.32**	0.17	0.22	0.12	0.12	0.04
	(-0.42)	(0.24)	(2.91)	(1.62)	(1.82)	(1.05)	(1.36)	(0.44)
NEGATIVE	0.57	0.85	1.32*	0.72	1.35*	0.76	0.19	0.08
	(1.03)	(1.26)	(2.18)	(1.18)	(2.21)	(1.31)	(0.30)	(0.12)

Table 3-3 presents the results of the multivariate logit regression using equation (4) for each one of the eight studied definitions of Accounting Betas (BACCs) for estimates based on 180 months for BMKT and 15 years for BACC. Standard errors are clustered by firm and year, as proposed by Petersen (2009). The dependent dummy variable is set to one if the Accounting Beta (BACC) is negative, or zero otherwise. The binary variable *VALUE* is one for those firms whose book-to-market ratio falls in the lowest quintile each year, or zero in all other cases. The dummy *NEGATIVE* is set to one when $BMKT_{180}$ is negative, and zero otherwise. *EBTA* is Earnings Before Interests, Taxes, Depreciations, and Amortizations (*EBITDA*) to Assets. *OITA* is *EBTA,* which is Earnings Before Interests, Taxes (EBIT) to Assets. *NITA* is Net Income to Assets. *FCTA* is Operational Cash Flow to Assets. *EBCE* is *EBITDA* to Equity. *OICE* is *EBIT* to Equity. *NICE* is Net Income to Equity. *CFCE* is Operational Cash Flow to Equity. Data on the balance sheet are from the beginning of the period. The first row in the table reports the coefficients and the second row reports the corresponding *t*-statistics (in parentheses).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3-4 Test of the difference between different measures of systematic risk

PANEL A. Somers' D Tests (in percentages)

	Item	BMKT	FCCE	FCTA	OICE	OITA	EBCE	EBTA	ROA
ROE	Somers' D	-25.90***	-1.65	15.24***	6.90***	15.50***	7.30***	8.98	28.23***
	Min	-28.33	-4.61	12.16	4.30	12.79	4.68	6.28	25.44
	Max	-23.44	1.31	18.30	9.49	18.18	9.91	11.66	30.97
ROA	Somers' D	-46.01***	-18.19***	-3.48*	-29.85***	0.61	-30.07***	-11.18***	
	Min	-47.83	-20.85	-6.21	-32.23	-1.79	-32.45	-13.57	
	Max	-44.14	-15.50	-0.74	-27.44	3.00	-27.65	-8.79	
EBTA	Somers' D	-41.04***	-11.23***	7.52***	-22.90***	30.21***	-20.86***		
	Min	-42.97	-13.98	4.79	-25.29	28.00	-23.28		
	Max	-39.08	-8.47	10.24	-20.47	32.39	-18.40		
EBCE	Somers' D	-22.00***	0.41	15.94***	-3.27**	27.39***			
	Min	-24.35	-2.47	13.00	-5.60	24.95			
	Max	-19.62	3.29	18.84	-0.93	29.81			
OITA	Somers' D	-47.67***	-17.76***	0.74	-30.70***				
	Min	-49.49	-20.47	-1.98	-33.08				
	Max	-45.81	-15.04	3.46	-28.28				
OICE	Somers' D	-22.19***	0.61	17.48***					
	Min	-24.53	-2.25	14.58					
	Max	-19.82	3.47	20.34					
FCTA	Somers' D	-43.30***	-28.84***						
	Min	-45.28	-31.29						
	Max	-41.27	-26.35						
FCCE	Somers' D	-25.04***							
	Min	-27.32							
	Max	-22.74							

PANEL B. Rank Test

Item	Ranking errors
Sum	23.38
Mean (%)	0.62
Median (%)	0.37
Sum	36.11
Mean (%)	0.96
Median (%)	0.47
Sum	29.88
Mean (%)	0.79
Median (%)	0.39
Sum	21.05
Mean (%)	0.79
Median (%)	0.39
Sum	35.02
Mean (%)	0.93
Median (%)	0.45
Sum	20.40
Mean (%)	0.54
Median (%)	0.34
Sum	36.13
Mean (%)	0.96
Median (%)	0.46
Sum	23.45
Mean (%)	0.62
Median (%)	0.38

Table 3-4 presents the test of the differences between BMKT and BACC. Panel A shows the results of the Somers' D test (Somers, 1962) for paired observations on the pooled sample. We test the null hypothesis of Column-variable - Row-variable = 0 for each combination. The first row presents the Somers' D coefficient, while the second and third rows correspond to the minimum and maximum of the *Confidence Interval* at a 95% confidence level. Panel B reports the output of the rank test. Rank errors are computed using the following equation: $E_t = ABS[\omega_t(BMKT) - \mu_t(BACC)]/N_t$, where ω_t is the ranking of this firm each year (*t*) sorted by BMKT, μ_t is the ranking sorted by BACC, and N_t is the yearly number of firms in the sample. *EBTA* is Earnings Before Interests, Taxes, Depreciations, and Amortizations (*EBITDA)* to Assets. *OITA* is *EBTA,* which is Earnings Before Interests, Taxes *(EBIT*) to Assets. *NITA* is Net Income to Assets. *FCTA* is Operational Cash Flow to Assets. *EBCE* is *EBITDA* to Equity. *OICE* is *EBIT* to Equity. *NICE* is Net Income to Equity. *CFCE* is Operational Cash Flow to Equity. All balance sheet data are from the beginning of the period.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix 3

Detailed explanation of the variable calculations

EBIT is Operating Income after Depreciation (COMPUSTAT # 178). *EBITDA* is Operating Income before Depreciation (# 13) if available, otherwise we use *EBIT* plus Depreciation and Amortization (# 14).

Operating Cash Flow is Net Cash Flow from Operating Activities (# 308) where available. If not, we use Operating Income after Depreciation (#178) minus Income Taxes (# 135) plus Depreciations (# 133) minus Total Current Accruals. Following Ogneva (2012), we define Total Current Accruals as the difference in Current Assets (# 4) minus the difference in Current Liabilities (# 5) minus the difference in Cash and Short-term Investments (# 1) plus the difference in Debt in Current Liabilities (# 34).

Following Daniel and Titman (2006), and Cohen *et al.* (2009), *Equity* is defined as Stock Holders' Equity (# 144) minus Preferred Stock plus Deferred Taxes (if available). If Stock Holders' Equity is missing, we compute it as Common Equity (# 60) plus Preferred Stock or Total Assets (# 120) minus Noncontrolling Interest (# 38) minus Total Liabilities (# 75). Preferred Stock is selected from the first non-missing option of Redemption Value (# 56), Liquidating Value (# 10), or Book Value (# 130). Deferred Taxes are taken from its Book Value (# 74) or Investment Tax Credit (# 208).

<u>Summary statistics of the subsample composed for positive estimates using 15 previous years and 180 months backwards</u>

In this appendix we present the descriptive statistics of the subsample used for compute Tables 3 and 4. In this subsample we drop negative $BMKT_{180}$ and $BACC_{15}$ estimates.

Table 3-5. Summary statistics of the subsample composed for positive estimates using 15 previous years and 180 months backwards

Stats	BMKT	ROE	ROA	EBTA	EBCE	OITA	OICE	FCTA	FCCE
N	9,929	10,869	10,514	9,863	10,591	9,976	9,378	9,259	14,855
Mean	1.07	1.61	1.47	1.08	1.64	1.07	1.72	1.18	0.88
Std. Dev.	1.32	1.72	1.53	1.12	1.72	1.09	1.87	1.25	0.40
p25	0.22	0.43	0.44	0.30	0.47	0.31	0.55	0.37	0.57
p50	0.61	1.09	1.03	0.71	1.13	0.72	1.17	0.79	0.88
p75	1.41	2.16	1.97	1.47	2.18	1.47	2.24	1.54	1.14

Table 3-5 shows the summary statistics of the calculated coefficients using a subsample composed by non-negative observations of both market beta based on previous 180 months and eight versions of Accounting Beta based on 15 years. Three last rows correspond to percentiles 25, 50 and 75 respectively. *EBTA* is *EBITDA* to Total Assets. *ROA* is *EBIT* to Total Assets. *NITA* is Net Income to Total Assets. *EBCE* is *EBITDA* to Equity. *OICE* is *EBIT* to Equity. *ROE* is Net Income to Equity. *FCTA* is Operating Cash Flow to Total Assets and *FCCE* is Operating Cash Flow to Equity. All balance sheet data are at beginning of the period.

Alternative estimation of the Logit model for negative BACC on firm characteristics

In this appendix we run an alternative regression of model 2. In this model, we use the values of book-to-market ratio (*BM*) and the logarithmic value of sales (*SALES*).

$$NBACC = \alpha_1 + \alpha_2 BM_{it} + \alpha_3 SALES_{it} + \alpha_4 NEGATIVE_{it} + \varepsilon_{it}$$

Table 3-6. Alternative estimation of the Logit model for negative BACC on Firm characteristics

	ROE	**ROA**	**EBTA**	**EBCE**	**OITA**	**OICE**	**FCTA**	**FCCE**
SIZE	-0.04	-0.05	-0.03	-0.05*	-0.03	-0.05	-0.05	-0.03
	(-2.63)	(-3.16)	(-1.87)	(-3.30)	(-1.97)	(-3.11)	(-2.98)	(-2.07)
BM	-0.00	-0.02	-0.03	-0.06	-0.03	-0.04	0.03	0.03
	(-0.06)	(-0.45)	(-1.00)	(-1.33)	(-0.86)	(-0.95)	(1.04)	(0.84)
NEGATIVE	-0.02	0.02	0.2	0.12	0.14	0.09	0.08	0.03
	(-0.34)	(0.29)	(2.96)	(1.85)	(1.89)	(1.25)	(1.54)	(0.63)

Table 3-6 presents the results of the multivariate logit regression using equation (4) for each one of the eight studied definitions of Accounting Beta (BACC) using a time window of 180 months for BMKT and 15 years for BACC. Standard errors are clustered by firm and year as proposed by Petersen (2009). The dependent dummy variable is set to one if the Accounting Beta (BACC) is negative or zero otherwise. The explanatory variables are log of sales (*SIZE*), book-to-market ratio *(BM)* and a dummy (*NEGATIVE*) set equal to one when $BMKT_{180}$ is negative and zero otherwise. First row in the table reports the coefficients and second row reports the corresponding t statistics (in parentheses).
* p<0.05, ** p<0.01, *** p<0.001.

CONCLUSIONS

This dissertation examines the different methods of estimating the systematic risk profile of private Firms (UFs) in order to identify more efficient ways of calculating their cost of equity capital (Ke). The analysis is conducted using two complementary approaches. In the first paper, we assess the empirical performance of the most common methods of estimating this risk, while introducing a novel model to compute Ke for UFs. Papers 2 and 3 examine some specific issues pertaining to the traditional models for computing the systematic risk of UFs.

The first paper begins with a modification to Campbell and Vuolteenaho's (2004) two-beta model (TBM) in order to ensure its applicability to UFs. This model is called Modified Two Beta Model – MTBM and it applies the proposed extension of Campbell et al. (2010) to capture the accounting return sensibility to long-term changes in consumption (CF), and the temporal variation in risk aversion (DR). Like Campbell et al.'s (2010), MTBM uses proxies to compute direct CF and DR. The relevant literature highlights three advantages of using proxies instead of the common decomposition approach: i) Decomposition approach is not applicable to UFs due to the unavailability of stock market prices, whereas the direct proxies method depends on accounting information that is available for UFs, ii) Unlike the decomposition approach, direct proxies are not questioned because of the validity of the VAR model estimate (Chen and Zhao (2009); Bianchi (2010); Maio (2013)), iii) The implementation of proxies seems to be less cumbersome than the decomposition approach since state variables are not required to be defined. Further, we further compare the empirical performance of MTBM with that of the three other commonly used methods in this field. These three methods include the accounting beta (BACC) introduced by (Beaver et al., 1970), the unleveraged beta method (PLB) suggested by Hamada (1972), and the operational betas (BOP) proposed by Mandelker and Rhee (1984). The four competing models were tested using a two-step test. First, Considerable research has been devoted to estimate the relationship between these methods and the Sharpe-Lintner CAPM Beta (BMKT). However, their performance in terms of applicability to the asset pricing model is not clear. This study contributes to the literature by assessing this performance. Our findings indicate that all studied methods, except BOP, are able to explain the stock returns, albeit with some limitations. While the poor empirical performance of BOP is contrary to the general findings of BOP-related literature, we attribute this difference to the fact that our dataset includes firms from all the economic sectors and not just the manufacturing sector. Second, a forecasting experiment is also conducted and its findings suggest that while BACC, PLB, and MTBM have some forecasting ability, they tend to under estimate future returns. However, a comparison of the expected properties of forecasting estimates indicates that MTBM provides the best results.

The second paper focuses on two issues of PLB. First, it addresses the unclear role of tax shields (TS) in the unleveraged/leveraged process; this problem has been discussed in the literature, but the findings are varied (Fernandez, (2004, 2005, 2007), Cooper and Nyborg (2006), and Fieten et al. (2005)). Second, a detailed examination of the performance of PLB when it substitutes BMKT in the computation of Ke, this aspect has not been adequately covered in previous research. We achieve these objectives by developing an analytical model that allows us to predict the behaviour of PLB and the error term (λ) in the estimation of the out-of-sample average of the risk class. In the absence of market imperfections and a correct risk classification (Hamada, 1972), PLB should be equal to BMKT, and λ should be a constant (i.e., equivalent to one). PLB is computed based on the common procedure deployed by practitioners. The process begins with the estimation of BMKT and follows by diminishing BMKT with the leverage ratio. The obtained individual unlevered betas are aggregated at the industry level by computing a yearly exogenous mean78. This mean is used to compute PLB by reapplying the specific leverage ratio of each firm. We compute four versions of PLB: two by including and excluding TS, and two others using book value and market value of equity. Although market value of equity is not relevant for UFs, it allows us to examine whether the TS affect the behaviour of PLB without information constraints. The relationships between all the versions of PLB and BMKT are assessed using a longitudinal approach controls for changes in the relationship over time and across different firms. The results suggest that including TS produces more robust empirical outcomes as suggested by Modigliani & Miller (1958, 1963), Cooper and Nyborg (2006) and Fieten et al. (2005) among others. Although it is clear that empirical findings cannot substitute theoretical arguments, this paper presents an unexplored point

[78] The firm's exogenous mean is defined as the average of the observations for all the firms in the industry/sector except that of the firm itself, in order to avoid possible endogeneity issues.

of view to the discussion. Our findings also indicate that there is a strong linkage between PLB and BMKT, therefore PLB usage is not misleading. Nevertheless, substituting BMKT with PLB may lead to an overestimation of Ke.

The last paper focuses on the BACC-BMKT relationship. It estimates a comprehensive range of possible BACC definitions across different time windows in order to determine whether using different accounting measures of return for estimating BACC affects its relationship with BMKT. The findings indicate that i) there is a pervasive link between BMKT and all the studied versions of BACC, ii) the link tends to increase monotonically when the time window for estimation is augmented, iii) the relationship seems to be stronger when BACC is calculated using accrual metrics (i.e., EBIT or Net Income) instead of cash flow related metrics. This result may explain why recent studies prefer accounting earnings rather than CF measures in the BACC analysis (Gebhardt et al. (2001), Nekrasov and Shroff (2009), Cohen et al. (2009)). Our study detects a large number of negative correlations between BMKT and BACC. A further examination of this problem suggests that these negative estimates are related to the size of the firm. Specifically, negative estimates are related with small firms. This may imply that BACC tends to exacerbate the well documented bias of BMKT in measuring the risk of these firms. This paper also measures the error produced by substituting BMKT by BACC. Somers' D test output shows that BACC overestimates the systematic risk by 20%–50% ($p < 0.05$). The errors are lower when BACC is estimated using earnings measures in the middle of the income statement (i.e., EBIT or EBITDA) scaled by equity.

A further assessment of the empirical findings of all the three papers reveals that the first paper essentially confirms the specific results reported in Papers 2 and 3. This alleviates possible queries about the implicit assumption in Papers 2 and 3 that the CAPM model is the correct method for estimating Ke. The overestimation of systematic risk when PLB and BACC are applied instead of BMKT is reported in all three papers. Moreover, the shortcomings of BACC and PLB in terms of their applicability to assessing small firms are also present in across all papers.

To summarise, this study aims to measure the empirical performance of existing methods for computing Ke for UFs. We contribute to the literature by proposing the MTBM method that seems to be a more efficient method for computing Ke for UFs than the traditional methods. Our study has yielded other relevant conclusions as well. i)

MTBM, BACC, and PLB are able to explain the average behaviour of stock returns with some limitations. On the contrary, it seems that BOP cannot be generalized to firms in economic sectors other than the manufacturing sector. ii) A comparison of the forecasting ability of MTBM, BOP, and PLB indicates that MTBM tends to produce more desirable results than BOP or PLB. iii) Practitioners' common method of computing Ke based on PLB seems to be unbiased since there is a strong correlation between BMKT and its substitute PLB. However, PLB is sensitive to the definition of the risk class. An aggrupation by size is required, beyond the concept of industrial classification by Hamada (1972). iv) A comparison of the different methods for estimating PLB indicates that the model proposed by Modigliani & Miller (1958, 1963) is the one that reports smaller differences and the strongest relationship with BMKT. v) BACC appears to be appropriate substitute for BMKT in the context of UFs; however, its application to small firms may produce small (or even negative) spurious results.

We acknowledge some limitations of our study. First, this study does not explore the models that use total risk instead of systematic risk (Godfrey and Espinosa (1996); Cañadas and Rojo Ramirez (2011)). Further, this study does not explore qualitative methodologies such as the analytical hierarchy process proposed by Cotner & Fletcher (2000) or the method suggested by St-Pierre & Bahri (2006) that employed non-financial measures as components of the BACC.

Similar to related literature, this study uses data for public firms since the fair values of UFs or approximations thereof are not available. In contrast, this fair value is easily available for traded stocks in the form of their market capitalization. Therefore, we take advantage of this fact, and analyse all the methods using the market capitalization as a target. This method has its own limitations since we are ignoring the liquidity premium (Officer, 2007), size effect (Van Dijk, 2011), and possible unique costs of UFs that may affect our findings. These limitations may be addressed in future research by using the propensity matching estimators combined along with the average treatment effect on the treated technique (Rosenbaum and Rubin, 1983) for comparing UFs and listed companies. This technique is being increasingly used in financial economics Almeida *et al.* (2009) Campello *et al.* (2010). This study focuses only on the US market, which may be considered as a limitation. Future research may explore and test competing methods in other markets.

References

Almeida, H., Campello, M., Laranjeira, B., & Weisbenner, S. 2009. Corporate debt maturity and the real effects of the 2007 credit crisis: National Bureau of Economic Research.

Andrew, G. 2007. ***Financial Management; Principles and Practice***: Freeload Press, Inc.

Arzac, E., & Glosten, L. 2005. A reconsideration of tax shield valuation. ***European Financial Management***, 11(4): 453-461.

Baginski, S. P., & Wahlen, J. M. 2003. Residual income risk, intrinsic values, and share prices. ***The Accounting Review***, 78(1): 327-351.

Ball, R., Sadka, G., & Sadka, R. 2009. Aggregate earnings and asset prices. ***Journal of Accounting Research***, 47(5): 1097-1133.

Baltagi, B. H. 2005. ***Econometric analysis of panel data***: J. Wiley & Sons.

Barton, J., Hansen, T. B., & Pownall, G. 2010. Which performance measures do investors around the world value the most and why? ***The Accounting Review***, 85(3): 753-789.

Beaver, W., Kettler, P., & Scholes, M. 1970. The association between market determined and accounting determined risk measures. ***The Accounting Review***, 45(4): 654-682.

Beaver, W., & Manegold, J. 1975. The association between market-determined and accounting-determined measures of systematic risk: some further evidence. ***The Journal of Financial and Quantitative Analysis***, 10(2): 231-284.

Beuselinck, C., & Manigart, S. 2007. Financial reporting quality in private equity backed companies: The impact of ownership concentration. ***Small Business Economics***, 29(3): 261-274.

Bianchi, F. 2010. Rare events, financial crises, and the cross-section of asset returns. ***Economics Research Initiatives at Duke (ERID) Working Paper***(41).

Black, F., Jensen, M., & Scholes, M. 1972. ***The capital asset pricing model: Some empirical tests***: Praeger Publishers.

Bowman, R. 1979. The theoretical relationship between systematic risk and financial (accounting) variables. ***The Journal of Finance***, 34(3): 617-630.

Bowman, R. 1980. The importance of a market-value measurement of debt in assessing leverage. ***Journal of Accounting Research***, 18(1): 242-254.

Bowman, R., & Bush, S. 2006. Using comparable companies to estimate the betas of private companies. ***Journal of Applied Finance***, 16(2): 71-81.

Bowman, R., Bush, S., & Graves, L. 2005. Estimating betas using comparable company analysis: is it a reliable method? ***JASSA***(1): 10-12,14,23.

Bowman, R., & Graves, L. 2004. A test of the usefulness of comparable company analysis in Australia. ***Accounting Research Journal***, 17(Special issue): 121-135.

Brimble, M., & Hodgson, A. 2007. Assessing the risk relevance of accounting variables in diverse economic conditions. ***Managerial Finance***, 33(8): 553-573.

Brown, P., & Walter, T. 2013. The CAPM: theoretical validity, empirical intractability and practical applications. ***Abacus***, 49(S1): 44-50.

Burgstahler, D. C., Hail, L., & Leuz, C. 2006. The importance of reporting incentives: earnings management in European private and public firms. ***The Accounting Review***, 81(5): 983-1016.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. 2006. Robust Inference with Multi-way Clustering. ***National Bureau of Economic Research Technical Working Paper Series***, No. 327.

Campbell, J., & Mei, J. 1993a. Where do betas come from? Asset price dynamics and the sources of systematic risk. ***Review of Financial Studies***, 6(3): 567-592.

Campbell, J., Polk, C., & Vuolteenaho, T. 2010. Growth or glamour? fundamentals and systematic risk in stock returns. ***Review of Financial Studies***, 23(1): 305-344.

Campbell, J. Y. 1991. A variance decomposition for stock returns. ***Economic Journal***, 101(405): 157-179.

Campbell, J. Y., & Mei, J. 1993b. Where do betas come from? asset price dynamics and the sources of systematic risk. ***The Review of Financial Studies***, 6(3): 567-592.

Campbell, J. Y., & Vuolteenaho, T. 2004. Bad beta, good beta. ***American Economic Review***, 94(5): 1249-1275.

Campello, M., Graham, J. R., & Harvey, C. R. 2010. The real effects of financial constraints: Evidence from a financial crisis. ***Journal of Financial Economics***, 97(3): 470-487.

Cañadas, J. A., & Rojo Ramirez, A. A. 2011. The Discount Rate in Valuing Privately Held Companies. ***Business Valuation Review***, 30(2): 70-81.

Chen, L., & Zhao, X. L. 2009. Return decomposition. ***Review of Financial Studies***, 22(12): 5213-5249.

Chung, K. H. 1989. The impact of the demand volatility and leverages on the systematic risk of common stocks. ***Journal of Business Finance & Accounting***, 16(3): 343-360.

Cochrane, J. H. 2011. Presidential Address: Discount Rates. ***The Journal of Finance***, 66(4): 1047-1108.

Cohen, R., Polk, C., & Vuolteenaho, T. 2003. The value spread. ***The Journal of Finance***, 58(2): 609-642.

Cohen, R., Polk, C., & Vuolteenaho, T. 2009. The price is (almost) right. ***Journal of Finance***, 64(6): 2739-2782.

Collins, D. W., Kothari, S. P., Shanken, J., & Sloan, R. G. 1994. Lack of timeliness and noise as explanations for the low contemporaneuos return-earnings association. ***Journal of Accounting and Economics***, 18(3): 289-324.

Cooper, I., & Nyborg, K. 2006. The value of tax shields is equal to the present value of tax shields. ***Journal of Financial Economics***, 81(1): 215-225.

Cotner, J. S., & Fletcher, H. D. 2000. Computing the Cost of Capital for Privately Held Firms. ***American Business Review***, 18(2): 27-33.

Da, Z., Guo, R.-J., & Jagannathan, R. 2012. CAPM for estimating the cost of equity capital: Interpreting the empirical evidence. ***Journal of Financial Economics***, 103(1): 204-220.

Damodaran, A. 2010. ***Applied Corporate Finance***: John Wiley & Sons.

Daniel, K., & Titman, S. 2006. Market reactions to Tangible and intangible information. ***The Journal of Finance***, 61(4): 1605-1643.

Dechow, P. M. 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. ***Journal of Accounting and Economics***, 18(1): 3-42.

Don, M. C. 1982. Evidence on a simplified model of systematic risk. ***Financial Management***, 11(3): 53-63.

Driscoll, J. C., & Kraay, A. C. 1998. Consistent covariance matrix estimation with spatially dependent panel data. ***Review of Economics and Statistics***, 80(4): 549-560.

Ehrhardt, M., & Brigham, E. 2009. ***Corporate Finance: A Focused Approach***: South-Western/Cengage Learning.

Engsted, T., Pedersen, T. Q., & Tanggaard, C. 2012. Pitfalls in VAR based return decompositions: A clarification. ***Journal of Banking & Finance***, 36(5): 1255-1265.

Faff, R. W., Brooks, R. D., & Kee, H. Y. 2002. New evidence on the impact of financial leverage on beta risk: a time-series approach. ***The North American Journal of Economics and Finance***, 13(1): 1-20.

Fama, E. F. 1970. Efficient capital markets: a review of theory and empirical work. ***The Journal of Finance***, 25(2): 383-417.

Fama, E. F., & French, K. R. 1993. Common risk factors in the returns on stocks and bonds. ***Journal of Financial Economics***, 33(1): 3-56.

Fama, E. F., & French, K. R. 1996. Multifactor Explanations of Asset Pricing Anomalies. ***The Journal of Finance***, 51(1): 55-84.

Fama, E. F., & French, K. R. 1997. Industry Costs of Equity. ***Journal of Financial Economics***, 43(2): 153-193.

Fama, E. F., & French, K. R. 2002. Testing Trade-Off and Pecking Order Predictions about Dividends and Debt. ***The Review of Financial Studies***, 15(1): 1-33.

Fama, E. F., & French, K. R. 2004. The capital asset pricing model: Theory and evidence. ***Journal of Economic Perspectives***, 18(3): 25-46.

Fama, E. F., & French, K. R. 2008. Dissecting anomalies. ***The Journal of Finance***, 63(4): 1653-1678.

Fama, E. F., & MacBeth, J. D. 1973. Risk, return, and equilibrium: empirical tests. ***Journal of Political Economy***, 81(3): 607-636.

Fernandez, P. 2002. The correct value of tax shields. ***Unpublished paper. IESE Business School. Available at 10.2139/ssrn.330541***.

Fernandez, P. 2004. The value of tax Shields is not equal to the present value of tax shields. ***Journal of Financial Economics***, 73(1): 145-165.

Fernandez, P. 2005. Reply to "comment on the value of tax shields is not equal to the present value of tax shields". ***The Quarterly Review of Economics and Finance***, 45(1): 188-192.

Fernandez, P. 2007. A more realistic valuation: adjusted present value and WACC with constant book leverage ratio. ***Journal of Applied Finance***, 17(2): 13-20.

Fieten, P., Kruschwitz, L., Laitenberger, J., Löffler, A., Tham, J., Vélez-Pareja, I., & Wonder, N. 2005. Comment on "the value of tax shields is not equal to the present value of tax shields". ***The Quarterly Review of Economics and Finance***, 45(1): 184-187.

Gebhardt, W. R., Lee, C. M. C., & Swaminathan, B. 2001. Toward an Implied Cost of Capital. ***Journal of Accounting Research***, 39(1): 135-176.

Godfrey, S., & Espinosa, R. 1996. A PRACTICAL APPROACH TO CALCULATING COSTS OF EQUITY FOR INVESTMENTS IN EMERGING MARKETS. ***Journal of Applied Corporate Finance***, 9(3): 80-90.

Gonedes, N. J. 1973a. Evidence on the information content of accounting numbers: Accounting-based and market-based estimates of systematic risk. ***The Journal of Financial and Quantitative Analysis***, 8(3): 407-443.

Gonedes, N. J. 1973b. Properties of accounting numbers: Models and tests. ***Journal of Accounting Research***, 11(2): 212-237.

Gonedes, N. J. 1975. A note on accounting-based and market-based estimates of systematic risk. ***The Journal of Financial and Quantitative Analysis***, 10(2): 355-365.

Gow, I., Ormazabal, G., & Taylor, D. 2010. Correcting for cross-sectional and time-series dependence in accounting research. ***Accounting Review***, 85(2): 483-512.

Graham, J. R., & Harvey, C. R. 2001. The theory and practice of corporate finance: evidence from the field. ***Journal of Financial Economics***, 60(2-3): 187-243.

Griffin, H. F., & Dugan, M. T. 2003. Systematic risk and revenue volatility. ***Journal of Financial Research***, 26(2): 179-189.

Hamada, R. S. 1972. The effect of the firm's capital structure on the systematic risk of common stocks. ***The Journal of Finance***, 27(2): 435-452.

Harris, R. S., & Pringle, J. J. 1985. Risk-adjusted discount rates-extensions from the average-risk case. ***Journal of Financial Research***, 8(3): 237.

Harvey, C. R. 1989. Time-varying conditional covariances in tests of asset pricing models. ***Journal of Financial Economics***, 24(2): 289-317.

Hill, N. C., & Stone, B. K. 1980. Accounting betas, systematic operating risk, and financial leverage: A risk-composition approach to the Ddeterminants of systematic risk. ***Journal of Financial & Quantitative Analysis***, 15(3): 595-637.

Hoechle, D. 2007. Robust standard errors for panel regressions with cross-sectional dependence. ***Stata Journal***, 7(3): 281-312.

Hope, O.-K., Thomas, W. B., & Vyas, D. 2013. Financial reporting quality of U.S. private and public firms. ***The Accounting Review***, 88(5): 1715-1742.

Ismail, B. E., & Moon, K. K. 1989. On the association of cash flow variables with market risk: Further evidence. ***The Accounting Review***, 64(1): 125-136.

Jenkins, D. S., Kane, G. D., & Velury, U. 2009. Earnings conservatism and value relevance across the business cycle. ***Journal of Business Finance & Accounting***, 36(9-10): 1041-1058.

Johnson, M. 1999. Business cycles and the relation between security returns and earnings. ***Review of Accounting Studies***, 4(2): 93-117.

Johnstone, D. J. 2013. The CAPM debate and the logic and philosophy of finance. ***Abacus***, 49: 1-6.

Katz, S. P. 2009. Earnings quality and ownership structure: The role of private equity sponsors. ***The Accounting Review***, 84(3): 623-658.

Kemsley, D., & Nissim, D. 2002. Valuation of the debt tax shield. ***Journal of Finance***, 57(5): 2045-2073.

Kolari, J. W., & Velez-Pareja, I. 2012. Corporation income taxes and the cost of capital: a revision. ***Innovar - Revista de Ciencias Administrativas y Sociales***, 22(46): 53-71.

Koller, T., McKinsey, Inc., C., Goedhart, M., Wessels, D., Lastmckinsey, & Inc, C. 2010. ***Valuation: Measuring and Managing the Value of Companies***: John Wiley & Sons.

Krishnamurti, C., & Vishwanath, C. R. 2009. ***Advanced Corporate Finance***: Prentice-Hall of India Pvt. Ltd.

Kruschwitz, L., & Löffler, A. 2006. ***Discounted cash flow: a theory of the valuation of firms***: John Wiley.

Lettau, M., & Ludvigson, S. 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying
arying. ***Journal of Political Economy***, 109(6): 1238-1287.

Lev, B. 1989. On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research. ***Journal of Accounting Research***, 27: 153-192.

Lev, B., & Sunder, S. 1979. Methodological issues in the use of financial ratios. ***Journal of Accounting and Economics***, 1(3): 187-210.

Levy, H. 2010. The CAPM is alive and well: A review and synthesis. ***European Financial Management***, 16(1): 43-71.

Lewellen, J., & Nagel, S. 2006. The conditional CAPM does not explain asset-pricing anomalies. ***Journal of Financial Economics***, 82(2): 289-314.

Li, K., & Zhao, X. 2008. Asymmetric information and dividend policy. ***Financial Management***, 37(4): 673-694.

Maio, P. 2013. Return decomposition and the Intertemporal CAPM. ***Journal of Banking & Finance***, 37(12): 4958-4972.

Mandelker, G. N., & Rhee, S. G. 1984. The Impact of the degrees of operating and financial leverage on systematic risk of common stock. ***Journal of Financial & Quantitative Analysis***, 19(1): 45-57.

Marston, F., & Perry, S. 1996. Implied penalties for financial leverage: theory versus empirical evidence. ***Quarterly Journal of Business & Economics***, 35(2): 77-97.

Massari, M., Roncaglio, F., & Zanetti, L. 2008. On the equivalence between the APV and the WACC approach in a growing leveraged firm. ***European Financial Management***, 14(1): 152-162.

Mensah, Y. 1992. Adjusted accounting beta, operating leverage and financial leverage as determinants of market beta: A synthesis and empirical evaluation. ***Review of Quantitative Finance and Accounting***, 2(2): 187-203.

Miles, J., & Ezzell, J. 1985. Reformulating tax shield valuation: a note. ***Journal of Finance***, 40(5): 1485-1492.

Modigliani, F., & Miller, M. 1958. The cost of capital, corporation finance and the theory of Investment. ***The American Economic Review***, 48(3): 261-297.

Modigliani, F., & Miller, M. 1963. Corporate income taxes and the cost of capital: a correction. ***The American Economic Review***, 53(3): 433-443.

Mulford, C. 1985. The importance of a market value measurement of debt in leverage ratios: replication and extensions. ***Journal of Accounting Research***, 23(2): 897-906.

Nekrasov, A., & Shroff, P. K. 2009. Fundamentals-based risk measurement in valuation. ***Accounting Review***, 84(6): 1983-2011.

Newey, W. K., & West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. ***Econometrica***, 55(3): 703-708.

Newson, R. 2006. Confidence intervals for rank statistics: Somers' D and extensions. ***Stata Journal***, 6(3): 309-334.

Officer, M. S. 2007. The price of corporate liquidity: Acquisition discounts for unlisted targets. ***Journal of Financial Economics***, 83(3): 571-598.

Ogneva, M. 2012. Accrual Quality, Realized Returns, and Expected Returns: The Importance of Controlling for Cash Flow Shocks. ***The Accounting Review***, 87(4): 1415-1444.

Ohlson, J. A. 1979. Risk, Return, Security-Valuation and the Stochastic Behavior of Accounting Numbers. ***The Journal of Financial and Quantitative Analysis***, 14(2): 317-336.

Parrino, R., & Kidwell, D. 2009. ***Fundamentals of Corporate Finance***: John Wiley & Sons.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: comparing approaches. ***Review of Financial Studies***, 22(1): 435-480.

Pettit, J. 2007. ***Strategic corporate finance: applications in valuation and capital structure***: John Wiley & Sons.

Private Equity Growth Capital Council. 2013. Private Equity Performance Update.

Richardson, S., Tuna, I., & Wysocki, P. 2010. Accounting Anomalies and Fundamental Analysis: A Review of Recent Research Advances. ***Journal of Accounting and Economics***, 50(3): 410-454.

Roll, R., & Ross, S. A. 1994. On the cross-sectional relation between expected returns and betas. ***The Journal of Finance***, 49(1): 101-121.

Rosenbaum, P. R., & Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. ***Biometrika***, 70(1): 41-55.

Ross, S., Westerfield, R., & Jaffe, J. 2012. ***Corporate Finance***: McGraw-Hill Education.

Rubinstein, M. 1973. A mean-variance synthesis of corporate financial theory. ***The Journal of Finance***, 28(1): 167-181.

Schlueter, T., & Sievers, S. 2011. Determinants of market beta: the impacts of firm-specific accounting figures and market conditions. ***Review of Quantitative Finance and Accounting***: 1-36.

Simin, T. 2008. The Poor Predictive Performance of Asset Pricing Models. ***Journal of Financial & Quantitative Analysis***, 43(2): 355-380.

Somers, R. H. 1962. A new asymmetric measure of association for ordinal variables. ***American Sociological Review***, 27(6): 799-811.

St-Pierre, J., & Bahri, M. 2006. The use of the Accounting beta as an Overall Risk Indicator for Unlisted Companies. ***Journal of Small Business and Enterprise Development***, 13(4): 546-560.

Stein, J. C. 1996. Rational Capital Budgeting In An Irrational World. ***The Journal of Business***, 69(4): 429-455.

Subrahmanyam, A. 2010. The Cross-Section of Expected Stock Returns: What Have We Learnt from the Past Twenty-Five Years of Research? ***European Financial Management***, 16(1): 27-42.

Taggart, R. 1991. Consistent valuation and cost of capital expressions with corporate and personal taxes. ***Financial Management***, 20(3): 8-20.

Tham, J., & Vélez-Pareja, I. 2004. ***Principles of cash flow valuation*** London: Elsevier Academic Press.

Thompson, S. B. 2011. Simple formulas for standard errors that cluster by both firm and time. ***Journal of Financial Economics***, 99(1): 1-10.

Van Dijk, M. A. 2011. Is size dead? A review of the size effect in equity returns. ***Journal of Banking & Finance***, 35(12): 3263-3274.

Vuolteenaho, T. 2002. What drives firm-level stock returns? ***The Journal of Finance***, 57(1): 233-264.

Wang, J., Meric, G., Liu, Z., & Meric, I. 2009. Stock market crashes, firm characteristics, and stock returns. ***Journal of Banking & Finance***, 33(9): 1563-1574.

Wang, K., Li, J., & Huang, S. 2012. Bad beta good beta, state-space news decomposition and the cross-section of stock returns. ***Accounting & Finance***, 53(2): 587–607.

World Bank. 2013. World development indicators: World Bank.

Zhang, X. 2006. Information uncertainty and stock returns. ***The Journal of Finance***, 61(1): 105-137.