Determinants of Market Beta:

The Impacts of Firm-Specific Accounting Figures and Market Conditions

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Abstract: This article examines and extends research on the relation between the capital asset pricing model (CAPM) market beta, accounting risk measures and macroeconomic risk factors. We develop a beta decomposition approach, that nests competing models with different business risk proxies and allows for theoretical cross-model comparison. Because model tests require estimated independent variables, resulting in measurement error, we empirically estimate three comparable model specifications with instrumental variable estimators and for the first time provide thorough instrument diagnostics in this setting. Correcting for the heretofore neglected weak instruments problem, we find that growth risk (i.e. the risk of firm sales variations that are inconsistent with the market wide trends), is the business risk that explains cross-sectional variations in market beta best.

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1. Introduction

Measuring and understanding the cost of capital is one of the fundamental problems in corporate finance. The best-researched framework is the capital asset pricing model (CAPM) and its beta factor (Sharpe 1964, Lintner 1965). Although the extant literature has often challenged the validity and the importance of this model (notably Fama/French, 1992), recent research indicates that the CAPM provides important insights and is essential to understanding and estimating the cost of capital for firms (Levy/Roll 2010, Levy 2010, Zhi/Guo/Jagannathan 2009, Ray/Savin/Tiwari 2009). Given the tremendous importance of systematic risk in the form of the market beta, this article examines and extends research on the relation between the CAPM market beta, accounting risk measures and macroeconomic risk factors.

Although prior literature acknowledges the impacts of financial- and operating leverage on market beta (e.g. Mandelker/Rhee 1984, Gahlon/Gentry 1982, Hill/Stone 1980), research meanwhile finds that intrinsic business risk (i.e., the demand volatility of a firm's output due to macroeconomic conditions) is the main component of market beta (e.g., Dugan/Griffin 2003, Mensah 1992, Chung 1989). Nevertheless how to appropriately capture and measure business risk remains unclear.

One key conjecture is that business risk is best captured by growth (i.e., the uncertainty of a firm's output in comparison to market movements (Penman 2010)). For a given level of financial leverage and asset turnover, a firm's growth will be driven by changes in its sales.

Consequently, when one is measuring a firm's growth characteristics relative to those of its market competitors, growth risk is driven by the risk that firm sales growth will deviate from market wide dynamics. Therefore, the covariance of firm sales with market-wide sales trends, which serves as a proxy for market output, should be a key determinant of market beta, and the associated risk will be referred to as growth risk.

While this reasoning has economic and intuitive appeal, the literature points out the effect of varying term structure and yield effects on financially leveraged firms and their perceived systematic risk (e.g., Campello/Chen/Zhang 2008, Jagannathan/Wang 1996, Chen/Roll/Ross 1986). This strand of the literature argues that all firms face the same risk in form of exogenous shocks which affect the whole economy. Their research suggests that market-wide interest rate spreads (i.e., the spread between long- and short-term interest rates or the spread between high- and low-grade bond returns) have a significant effect on a firm's output, as measured by firm sales, and thus affects systematic risk. This economic reasoning leads to the competing business risk proxy spread risk, which captures the reaction of firm sales to market-wide interest rate spreads. Thus, this paper first addresses the question of which of these two factors best explains the cross-sectional variation in systematic risk.

Furthermore, closely intertwined with this research question is the issue of how growth risk is measured from an accounting perspective. Theoretical considerations indicate that the further decomposition of growth risk into income risk, which is related to firm profitability, and productivity risk, which captures firm efficiency, are possible. Naturally, the question arises of whether crude but potentially more robust proxies such as the covariance of firm sales with market-wide sales are preferable to a more detailed breakdown. Being precise, is it useful to decompose growth risk into the product of income- and productivity risk?

To answer these two questions we develop an extended beta decomposition approach that nests three models differing in terms of their suggested business risk factor. These insights provide the necessary basis for empirically identifying comparable model specifications we seek to address our research questions. In addition to standard ordinary least squares (OLS) estimation, we employ state-of-the-art instrumental variable (IV) estimators to cope with the main variables' measurement error. Using a wide range of instrument diagnostics and first-stage regression results, we detect and correct for hitherto unresolved problems arising from weak instrument identification.

Our results are as follows. Estimating the three models for the same sample of firms and the same time horizon using OLS shows that growth- and spread risk seem capable of explaining cross-sectional variation in market beta. In other words, ordinary least squares estimates are not sufficient to determine, whether growth- or spread risk is the key determinant of fundamental risk. However, based on estimation using the appropriate IV/GMM technique, only the growth- and income risk models remain intact. Turning to the question of whether it is worthwhile to decompose growth into more detailed components such as income- and productivity risk, we find this not to be the case because the measure of productivity is mostly not statistically significantly related to the cost of capital and because growth risk always provides better model fit.

These results provide strong empirical support for the framework outlined in Penman (2010), indicating that growth risk is a sufficient, reliable and robust proxy that explains differences in the cost of capital and is the most important determinant of fundamental risk.

Therefore, we contribute to the literature in two ways. First, we provide a comprehensive beta decomposition model that can guide researchers who need proxies which are closely related to a firm's cost of capital. Second, we empirically show that growth risk, as indicated by Penman (2010), is the most important component of systematic risk, has strong economic intuition and informs management about its importance with regard to firm cost of capital.

The remainder of this paper is structured as follows. The second section introduces our hypotheses, presents econometric concerns related to the main variables' measurement error, introduces our extended market beta decomposition approach and shows how it comprises our final model specifications. Section 3 introduces the sample and estimation techniques. Section 4 presents the empirical analysis, and Section 5 provides information on the robustness of the results. A final section concludes and discusses the limitations of the study.

2. Theoretical Considerations and Econometric Concerns

The CAPM proposes that the only type of non-diversifiable risk is market risk as a whole. The premium for a special investment is determined by the market portfolio risk premium and the investment's sensitivity to that risk, i.e., the market beta. Because the beta factor is defined in terms of expected stock returns and estimated using actual past returns, factors driving stock returns will interact with estimated market betas. Because stock prices can be represented as discounted expected dividends, returns will be affected by systematic factors that change the economy's discount rate or lead to revised expectations regarding the cash flows generated by a firm.

The literature consistently indicates that financial leverage (i.e., the degree to which a firm uses borrowed money) and operating leverage (i.e., the extent to which fixed costs and variable costs are used for production) impact market beta (Gahlon/Gentry 1982, Hill/Stone 1980, Lev 1974). In addition, economists have presented evidence that intrinsic business risk, which is defined as the volatile demand for firm output due to macroeconomic conditions, is the foremost component of market beta (e.g., Chung 1989, Mensah 1992, Griffin/Dugan 2003). However, prior studies differ in the macroeconomic variables that they use. Unforeseen changes in these variables affect pricing in the economy and lead to the revised valuation of perceived firm risk and of its relative position in the market. The literature also indicates how to best quantify the impact of changing macroeconomic conditions on a firm's fundamental figures. However, it remains unclear how to appropriately capture and measure business risk.

Penman (2004, 2010) argues that returns on a firm's equity are driven by the risk that equity will not increase as expected. For a given level of financial leverage and asset turnover, growth in equity will be driven by growth in sales. Indeed, Penman refers to sales risk as the foremost business risk affecting growth in and return on net operating assets and, ultimately, returns on equity. Lakonishok, Shleifer and Vishny (1994) provide empirical evidence consistent with Penman's theoretical assertions. Their findings indicate that high sales growth leads to significantly smaller stock returns than does low sales growth. Further, Davis (1994) highlights past sales growth as a main factor influencing stock returns. These findings are corroborated in recent work by Mohanram (2005) and Cooper, Gulen and Schill (2008).

Because this strand of literature argues that variability in sales is a main factor driving stock returns, this attribute should also help to explain market beta. If business risk is understood to be related to volatile demand for firm outputs due to macroeconomic conditions, the question arises of how to relate variability in firm sales to economy-wide factors that affect the firm's relative position in the market. Recalling the definition of market beta as risk associated with the covariability of a firm's stock returns with market returns, we can identify one straightforward business risk measure: the interaction between variations in firm sales and market-wide sales changes. Measuring market output in the same way as firm output demonstrates the direct relation between a firm's position and that of its competitors. Therefore, we introduce growth risk, defined as the risk associated with covariance in firm sales growth with changes in economy-wide sales, as our first business risk factor. This factor should be useful in explaining cross-sectional variation in market beta.

To measure macroeconomic conditions based on market output alone would mean neglecting the well-known fact that all firms in the economy face the risk of changing term-structure spreads or twists in the yield curve (Campello/Chen/Zhang 2008, Fama/French 1993). Unanticipated shifts in the riskless interest rate have an impact on stock pricing. Varying risk premiums of corporate bonds represent the degree of risk aversion of the economy in terms of interest spreads. These changes in market-wide interest spreads or rates lead to the revised valuation of future cash-flows, which in turn affects returns and, consequently, market beta. Furthermore, varying inflation rates influence nominal expected cash flows. Chen, Roll and Ross (1986) provide empirical evidence that those rates affect stock returns, whereas Fama and French (1993) underline these findings. According to their argument, there should be an overlap between stock and bond return processes, especially for integrated markets. The authors empirically show that factors in term structure and default risk – i.e., the spreads of corporate and government bond returns – have an impact on both bond and stock returns.

Whereas the concept of market beta allows us to evaluate a particular firm's stock returns in relation to the entire market in which the firm operates, macroeconomic variables that affect that market structure and therefore ultimately impact each firm's beta should also be of special interest. For example, consider the case of changing interest rate levels in the economy. More projects will become attractive as interest rates decline, and new competitors will be able to enter the market. In contrast, widening interest spreads for high- and low-grade borrowers will make business more difficult and unprofitable for low-quality firms, possibly resulting in business failure and market exit. Either market development will have an effect on a firm's relative position in the market and ultimately on its beta. Because we refer to business risk as the volatility in the demand for a firm's output due to macroeconomic conditions, we use the term "spread risk" to refer to the risk associated with the covariance of firm sales with a particular market interest rate spread.

Although the impact of interest rate spreads on market beta seems reasonable, we wish to emphasize that changing interest levels affect all firms in more or less the same manner. We anticipate finding evidence of a strong influence of changing interest spreads on market beta, but we recall based on the theoretical concept of market beta that each firm's position must be evaluated compared with that of its market competitors. Because growth risk directly positions a firm in competition with other market participants, we emphasize our first hypothesis:

H1: growth risk explains variations in market beta better than spread risk.

Although growth risk could be the dominating force in explaining the cross-sectional variation in market beta, sales might be a too crude figure to be informative. Sales are only an indirect proxy of a firm's earnings. However, it is reasonable to expect that changes in a firm's profitability due to changes in macroeconomic conditions will have a strong impact on beta. Furthermore, firms with more cost-efficient production technologies should incur lower cost of capital because of their greater shock-absorbing capabilities. As we will elaborate below in discussing our beta decomposition approach, theoretical considerations dictate the further segmentation of growth risk into income risk and productivity risk. Income risk is a firm's risk of volatile earnings captured as the covariance risk of a firm's accounting flows contrasted with macroeconomic conditions proxied by changes in market-wide sales. Productivity risk can be interpreted as a measure of changes in productivity over time. It expresses the effect of cost reduction investments that reduce risk and measures the effect of rising risk due to investments undertaken to expand a firm's market share or establish new products. Essentially, this variable measures the effect of changes in earnings on changes in firm sales.

Based on the idea that growth risk is a rather crude measure that must be further decomposed into factors indicating profitability as well as efficiency, we assume that the following holds true:

H2: The decomposition of growth risk into income risk and productivity risk helps to better explain market beta.

However, it remains unclear which of the first two empirical measures best captures intrinsic business risk and if measuring the sub-components of growth risk better explains cost of capital.

The purpose of our models is to provide a comprehensive and flexible approach to decomposing and explaining variations in market beta. These models mainly differ in the business risk factors that they consider. The first model is based on the interaction of firm sales with market-wide sales and is therefore labeled the growth risk model. The second model analyzes how a firm's output is influenced by interest rate spreads and is labeled the spread risk model. Finally, we introduce our income risk model, which further decomposes growth risk into income risk and productivity risk, exploring the risk of changes in firm income due to variations in market-wide sales and the risk of changes in production efficiency. The main goal of our process is to create models that nest the specifications highlighted in the prior literature (Chung 1989, Mensah 1992, Griffin/Dugan 2003).

Throughout the model derivation process, we use the following variables: $S_{i,t}$ are the sales of a firm i at time t, $NI_{i,t}$ is net income, $NOI_{i,t}$ is operating income, $E_{i,t}$ is equity market value and IS_t is the interest rate spread.

The CAPM yields the following for a firm's market beta:

$$\beta_{i,t} = Cov\left(R_{i,t}, R_{M,t}\right) / Var\left(R_{M,t}\right),$$

where $R_{i,t} = NI_{i,t} \big/ E_{i,t-1}$ is the return for firm i and $R_{M,t}$ is the corresponding market return. We simply expand beta's covariance formula and dissolve the variance term, showing that the CAPM beta formula equals[1]

$$\beta_{i,t} = \frac{E^2_{M,t-1}}{\frac{dNI^2_{M,t} \cdot S^2_{M,t-1}}{dS^2_{M,t}} \cdot Var(dS_{M,t} \big/ S_{M,t-1})} \cdot Cov\left(OpRisk_i \cdot FinRisk_i \cdot \frac{dNI_{i,t}}{E_{i,t-1}} \cdot \frac{dS_{i,t}}{dNI_{i,t}} \cdot \frac{NI_{i,t-1}}{S_{i,t-1}} \cdot \frac{dIS_t}{IS_{t-1}} \cdot \frac{IS_{t-1}}{dIS_t}, \frac{dNI_{M,t}}{E_{M,t-1}} \cdot \frac{NI_{M,t-1}}{NI_{M,t-1}} \cdot \frac{S_{M,t-1}}{S_{M,t-1}} \cdot \frac{dS_{M,t}}{dS_{M,t}} \right), \tag{1}$$

where 'd' denotes the difference operator. The variables 'operating risk' ($OpRisk_i$) and 'financial risk' ($FinRisk_i$) capture operating and financial leverage and are defined as[2]

Operating risk: $$OpRisk_i = \frac{dNOI_{i,t}}{NOI_{i,t-1}} \cdot \frac{S_{i,t-1}}{dS_{i,t}}$$

Financial risk: $$FinRisk_i = \frac{dNI_{i,t}}{NI_{i,t-1}} \cdot \frac{NOI_{i,t-1}}{dNOI_{i,t}}.$$

Next, we introduce the intrinsic business risk variables 'growth risk' ($GrRisk_i$), 'spread risk' ($SpRisk_i$), and 'income risk' ($InRisk_i$) together with the related factor 'productivity risk'

1 A step-by-step illustration of the derivation process and how this formula incorporates prior model specifications is available upon request.

2 See Mandelker/Rhee (1984) and Chung (1989).

($ProdRisk_i$), which create the main differences among the three models that we compare here. We define them as follows:

Growth risk: $$GrRisk_i = \frac{1}{Var\left(dS_{M,t} / S_{M,t-1}\right)} \cdot Cov\left(\frac{dS_{i,t}}{S_{i,t-1}}, \frac{dS_{M,t}}{S_{M,t-1}}\right)$$

Spread risk: $$SpRisk_i = \frac{dS_{i,t}}{S_{i,t-1}} \cdot \frac{IS_{t-1}}{dIS_t}$$

Income risk[3]: $$InRisk_i = \frac{1}{Var\left(dS_{M,t} / S_{M,t-1}\right)} \cdot Cov\left(\frac{dNI_{i,t}}{NI_{i,t-1}}, \frac{dS_{M,t}}{S_{M,t-1}}\right)$$

Productivity risk: $$ProdRisk_i = \frac{dS_{i,t}}{S_{i,t-1}} \cdot \frac{NI_{i,t-1}}{dNI_{i,t}}$$

Via deduction and by rearranging formula (1), we obtain the growth, spread and income risk models[4]:

i) The growth risk model[5]:

$$\beta_{i,t} = OpRisk_i \cdot FinRisk_i \cdot GrRisk_i \cdot \frac{NI_{i,t-1}}{E_{i,t-1}} \cdot \frac{dS_{M,t}}{S_{M,t-1}} \cdot \frac{E_{M,t-1}}{dNI_{M,t}}, \tag{2}$$

ii) The spread risk model:

$$\beta_{i,t} = OpRisk_i \cdot FinRisk_i \cdot SpRisk_i \cdot \frac{NI_{i,t-1}}{E_{i,t-1}} \cdot \frac{dS_{M,t}}{S_{M,t-1}} \cdot \frac{E_{M,t-1}}{dNI_{M,t}} \cdot \frac{1}{Var(dS_{M,t} / S_{M,t-1})} \cdot Cov\left(\frac{dIS_t}{IS_{t-1}}, \frac{dS_{M,t}}{S_{M,t-1}}\right) \tag{3}$$

and

iii) The income risk model:

[3] The decomposition of formula (1) indicates that the macroeconomic variable has to be market-wide sales. One might suggest that it should be market-wide earnings, but in unreported robustness tests, we use the latter option to estimate income risk and obtain equivalent results.

[4] Because all of our final models equal the CAPM market beta, the models are equivalent.

[5] Note that the factors $\left(dS_{M,t} / S_{M,t-1}\right) \cdot \left(E_{M,t-1} / dNI_{M,t}\right) \cdot \left(Var(dS_{M,t} / S_{M,t-1})\right)^{-1} \cdot Cov\left(dIS_t / IS_{t-1}, dS_{M,t} / S_{M,t-1}\right)$ and $\left(dS_{M,t} / S_{M,t-1}\right) \cdot \left(E_{M,t-1} / dNI_{M,t}\right)$ are not firm specific and thus are captured by constants in the regression analysis.

$$\beta_{i,t} = OpRisk_i \cdot FinRisk_i \cdot InRisk_i \cdot ProdRisk_i \cdot \frac{NI_{i,t-1}}{E_{i,t-1}} \cdot \frac{dS_{M,t}}{S_{M,t-1}} \cdot \frac{E_{M,t-1}}{dNI_{M,t}} \tag{4}$$

Comparing formulas (2) and (3), one notes immediately that the main difference between the growth and the spread risk models addresses the first research question (regarding whether business risk can best be explained by the deviations of firm sales growth from market trends or the effects of interest rate spreads on firm sales). The income risk model is obtained from formula (2) by further decomposing growth risk into income and productivity risk. Although it is easy to calculate growth risk, the use of income and productivity risk is theoretically appealing. To address our second research question, we must determine if the more detailed income risk model is better suited to explaining variations in beta.

In addition, a thorough re-examination of this topic seems warranted because prior studies use different research designs to tackle the inherent econometric problem of measurement error affecting the main components of the model. This problem arises because the variables of interest are unobservable and must be estimated in previous regressions first. Whereas Chung (1989) addresses the measurement error problem thoroughly by employing instrumental variable (IV) estimates and various grouping approaches based on different sorting practices, Mensah (1992) and Griffin/Dugan (2003) reject the IV approach and instead rely on a portfolio grouping approach. Recent research shows that the grouping technique is only a special, limited example of the IV approach (Batistatou/McNamee 2008). Therefore, the IV approach is the most appropriate means of addressing problems arising from the use of estimated independent variables that are subject to measurement error (Easton/Monahan 2005, Hausman 2001, Griliches 1986).

Furthermore, recent developments in econometrics allow for thorough tests of instrument validity and of the estimation techniques utilized (Baum/Schaffer/Stillman 2007, Murray 2006, Andrews/Stock 2005, Stock/Wright/Yogo 2002, Hahn/Hausman 2002). In addition, more powerful estimation techniques such as the generalized method of moments (GMM) technique have been derived that allow robust inference in these cases (Baum/Schaffer/Stillman 2007, Kleibergen 2005, Erickson/Whited 2002). Therefore, we empirically test our three model specifications using a sample of 212 firms for the years 1990 to 1999 via two-stage least squares and GMM. Furthermore, our extended instrument list allows us to provide thorough instrument diagnostics, i.e., under-, over- and weak-identification tests as well as broad first-stage regression results.

From the econometric perspective, our first-stage regressions show that the instruments are valid and relevant for all specifications. Furthermore, none of our specifications is under- or over-identified, which increases our confidence in the research design employed. However, we are also the first in this line of research to detect that all models suffer from the weak identification problem. Although there is no easy solution available, recent research comparing the power of several estimators with weakly identified equations finds that the IV estimator by Fuller (1977) is a robust alternative (Andrews/Stock 2005, Hahn/Hausman/Kuersteiner 2004, Wooldridge 2003). Employing the Fuller estimator, we again confirm the robustness of the growth and income risk results. Based on our main results and those of various other robustness tests, we find that growth risk is always ahead of spread risk for several time intervals and across different accounting flow concepts.

The next section describes how we estimate and empirically test each of the three market beta decompositions.

3. Data and Estimation Procedure

Our main sample consists of information regarding 212 firms reporting 10 years of non-missing data during the period from 1990 to 1999[6]. We obtain annual accounting data from the Compustat database[7] and monthly market data from the Center for Research in Security Prices (CRSP). We limit our estimation to non-financial firms[8]. The market model is used to estimate the CAPM market beta (β_i) of each common stock (i=1,…,212). This estimation is based on the S&P 500 value-weighted index return[9],

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{M,t} + \varepsilon_{i,t},$$

where i denotes the firm number (i =1,…, 212), t denotes time measured in months for market beta estimation, $R_{i,t}$ is the monthly stock return and $R_{M,t}$ the corresponding market return. $\varepsilon_{i,t}$ represents a disturbance term.

Because our proxies for business, operating and financial risk are not observable, they have to be estimated as well. We perform the following time series regression using ten years of data[10]:

$$\ln(X_{i,t}) = \alpha_{i,0} + \alpha_{i,1} \cdot \ln(Y_{i,t}) + \varepsilon_{i,t},$$

where $X_{i,t}$ and $Y_{i,t}$ denote the variables of interest for each risk proxy, $\alpha_{i,1}$ (i.e., the slope of the regression line) is the estimate of our desired risk proxy, $\alpha_{i,0}$ a constant, $\varepsilon_{i,t}$ a disturbance term and $\ln(\cdot)$ the natural logarithm.

6 Our robustness tests include varying time intervals for alternative 10-year time spans, which support our findings for 1990 to 1999. Further time intervals are 1980 to 1989, 1985 to 1994 and 1995 to 2004. In conducting an estimation using 10 years of annual data, we are consistent with the prior literature.

7 For details on the requested data, see Appendix 1.

8 Our results are robust to the inclusion of financial firms, but we recognize that the estimated risk proxies should be treated with care when comparing financial and non-financial firms.

9 All of our conclusions remain qualitatively unchanged if we use the S&P 500 equal-weighted index returns.

10 See also Mandelker/Rhee (1984).

When we estimate growth risk, $X_{i,t}$ represents firm sales and $Y_{i,t}$ market-wide sales[11]. Using this general estimation procedure, we use the following variables to estimate our risk proxies[12]:

	Risk proxy	**Variable applied for $X_{i,t}$**	**Variable applied for $Y_{i,t}$**
1	Growth risk	Sales	Market-wide sales
2	Spread risk	Sales	Interest rate spread[#]
3a	Income risk	Net income	Market-wide sales[##]
3b	Productivity risk	Sales	Net income
4	Financial risk	Net income	Operating income
5	Operating risk	Operating income	Sales

Notes:
Each of the five risk proxies is estimated via the above-described estimation procedure using the log of a firm-specific accounting variable and the log of a firm- or market-specific variable.
[#]The interest rate spread variable indicates the difference between the long- and short-term market-wide interest rates. We use returns on long-term government bonds and one-month Treasury bills as indicated in the H.15 Federal Reserve Statistical Release (see also Chen/Ross/Roll 1986, Fama/French 1993).
[##]With no theoretical justification regarding the beta decomposition approach, one might favor the use of market-wide net income as a macroeconomic variable for estimating income risk. In unreported robustness tests, we employ market-wide net income and obtain equivalent results.

growth and spread risk are easy to calculate because sales are reliably measurable. In contrast, income risk and productivity risk are more complicated because the necessary financial accounting data on net income and operating income may vary based on differing accounting practices used. Whereas accounting earnings and accruals are often better predictors of firm performance than cash flows (e.g., Dechow 1994), the corporate finance literature suggests cash flows to be a more meaningful measure of firm value and profitability than reported earnings. Instead of using data on net income and operating income directly, our analysis presents four different measures of accounting flow that are similar to cash flow and proxy firm profitability[13]. We take advantage of the accounting flows 'net income from operations' (NIOP), 'fund flow from operations'

[11] We apply aggregate market sales data provided by Reuters.

[12] We would like to note suggestions by O'Brien/Vanderheiden (1987) and Dugan/Shriver (1992), who propose the inclusion of a time trend for detrending the risk proxies' estimate. In unreported robustness tests, we include a time trend in our regressions. Our results remain qualitatively equal.

[13] See also Mensah (1992) and Ismail/Kim (1989).

(FFOP), 'working capital from operations' (WCOP) and 'cash flow from operations' (CFOP)[14]. Our main results are based on the most net-income-like NIOP accounting flow, which substitutes for the financial income statements of each firm[15].

All models include the variable 'income to equity' ($I\_to\_E_{i,t} = NI_{i,t} / E_{i,t-1}$). We compute 'income to equity' as the average value of the ratios between net income and net equity market value from 1990 to 1999. Because our estimation procedure involves using the natural logarithm of each accounting variable, we require data from income statements to be strictly positive for each firm during the 10-year estimation period[16].

Table 1 provides summary statistics for all estimated risk proxies and the variable 'income to equity' distributed over eleven industries using Fama/French's 12-Industry Portfolio Sic Classification[17].

----Please insert Table 1 approximately here----

After estimating all risk proxies, we perform the following logarithmic transformation of equations (2), (3) and (4) to estimate our growth, spread and income risk models:

$$\ln(\beta_i) = \gamma_0 + \gamma_1 \ln(\mathrm{GrRisk}_i) + \gamma_2 \ln(\mathrm{FinRisk}_i) + \gamma_3 \ln(\mathrm{OpRisk}_i) + \gamma_4 \ln(\mathrm{I\_to\_E}_i) + e_i \quad (5)$$

$$\ln(\beta_i) = \gamma_0 + \gamma_1 \ln(\mathrm{InRisk}_i) + \gamma_2 \ln(\mathrm{ProdRisk}_i) + \gamma_3 \ln(\mathrm{FinRisk}_i) + \gamma_4 \ln(\mathrm{OpRisk}_i) + \gamma_5 \ln(\mathrm{I\_to\_E}_i) + e_i \quad (6)$$

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14 For details regarding accounting flow calculations, see Appendix 2.

15 In the robustness section, we report estimation results for the FFOP and WCOP Accounting Flow for various time intervals. Unreported results for CFOP are qualitatively similar.

16 We are aware that some loss of generality arises when positive financial accounting data are required. One solution is to include firms with negative income statements and then simply add a positive constant to each observation sufficiently large that all negative numbers become greater than zero. However, this transformation assumes linearity, which might not hold true. Furthermore, adding an arbitrary positive number impedes interpretation and leads to subjective estimation results in the instrumental variable approach.

17 Recall that financials (included in Fama/French's classification code 11) are dropped.

$$\ln(\beta_i) = \gamma_0 + \gamma_1 \ln(\text{SpRisk}_i) + \gamma_2 \ln(\text{FinRisk}_i) + \gamma_3 \ln(\text{OpRisk}_i) + \gamma_4 \ln(\text{I\_to\_E}_i) + e_i \tag{7}$$

First, we estimate the equations using standard OLS. Because the variables are measured with error, the OLS results will likely be downward biased due to the negative correlation between the measurement error and the true, unobservable value of each variable. Therefore, we introduce the instrumental variable technique to reduce the bias of the OLS estimation. The incorporated instrumental variables should be highly correlated with the independent model variables but can be observed independently. Each independent variable is instrumented according to Appendix 3.

Panel A of Table 2 presents pairwise correlations of the estimated variables, whereas Panel B of Table 2 presents correlations for the instruments used.

----Please insert Table 2 approximately here---

4. Basic econometric analysis and main results

This section reports the main results for the determinants of market beta, including the results of the two competing growth and spread risk models as well as the further decomposition of growth risk into income- and productivity risk. Estimating equations (2), (3) and (4) requires careful consideration in order to move from the theoretical to the empirical domain. Because our independent variables of interest, most notably each model's intrinsic business risk factor, are unobservable and therefore have to be estimated, they are measured with error. Thus, the appropriate estimation techniques are instrumental variable techniques, either the classical two-stage least squares approaches (2SLS) or Hansen's (1982) more common generalized method of moments (GMM) technique. However, while theoretically appealing, the latter requires careful instrument specification, which is probably one of the most difficult tasks in applied empirical research. Thus, as noted in many studies, the use of instrumental variable techniques may be worth compared to the risk of biased coefficient estimates associated with regressions based on ordinary least squares (OLS). Hence, before we discuss our use of more sophisticated techniques, including those that represent recent advancements in the econometrics literature, we first report traditional OLS results for our three competing models (see Table 3).

----Please insert Table 3 approximately here----

For the sake of completeness, Table 3 includes two restricted models. The first of these models sets the intrinsic business risk proxies (growth, spread and income risk) equal to zero, emphasizing that productivity risk, even on its own, does not explain beta. Hereafter we also set productivity risk equal to zero because, according to the influential study by Mandelker and

Rhee (1984), this variable should be captured by the constant in the regression estimates. To address our first research question, we ask if each intrinsic business risk variable (i.e., so-called growth, spread, income and productivity risk) adds significant explanatory power to the model specification. This is clearly the case, as indicated by the p-values of the Wald test in Table 3. In other words, any model specification including any of the proposed intrinsic business risk proxies performs significantly better than the restricted model comprised of only financial and operating risk.

The coefficient estimates of the three models show that each intrinsic business risk proxy is statistically significant in the predicted direction. Although the estimates for the growth and income risk model are similar (0.30 vs. 0.33), the proxy for spread risk is significantly smaller (0.14). Furthermore, our estimations show that financial and operating risk perform only partly as expected. In particular, financial risk has an unexpected negative coefficient in all three specifications. The same issue arises with the coefficient of operating risk in the income risk model, although it is not statistically significantly different from zero (-0.05). Based on the overall coefficient estimates, we conclude that the model in which growth risk is used as the proxy for intrinsic business risk performs best. Here, all coefficient estimates have the predicted signs or (in the case of financial risk) are not statistically significantly different from zero. Turning to our main analysis – i.e., the model comparison – we find that the growth risk model has the highest adjusted R-squared (0.39) and the smallest BIC (250.36), which indicates that this is best model specification. This finding is confirmed by formally applying Vuong's (1989) discrimination test for overlapping models and by testing the differences between the growth risk model and the spread risk model in terms of model fit based on the Vuong test statistic (see Appendix 4 for details). However, we cannot significantly differentiate between the income risk model and the growth risk model (Vuong test statistic: 1.67). Therefore, we also use a BIC discrimination test for model selection. Along with Augustin, Sauerbrei and Schumacher (2005), Buckland, Burnham and Augustin (1997) and Jeong (2008), we generate an empirical distribution for the model selection criterion BIC using bootstrap methods. Applying a t-test, we test the null hypothesis that the growth risk model's BIC is significantly greater than or equal to the BIC for the other two models. Rejecting the null in each case at the 1% level, we confirm the model selection results indicating that growth risk is superior to spread risk. However, using the BIC discrimination, we also find that the growth risk model has significantly better fit than the income risk model including productivity risk.

Overall, the OLS regression results clearly indicate that the growth risk model is the most parsimonious and best model of intrinsic business risk. This finding provides the first evidence that our first research hypothesis is valid, although we do not find evidence to support the second hypothesis.

However, given the above concerns regarding measurement error, the results may be of limited use, since coefficient estimates are likely to be biased downwards (Hausman 2001). Therefore, instrumental variables are used. We identify several observable variables which are supposed to be highly correlated with the economic construct of our accounting risk measure. They are defined and calculated according to Appendix 3.

First, for the instrumentation of growth risk, we use the standard deviation of firm sales and the average growth in firm sales during the estimation period. We assume those measurable variables to be consistent with the idea of growth risk as capturing the reaction of firm sales to changes in aggregate market sales. Our first-stage regression analysis yields that the instrumentation of spread risk is more difficult compared to the use of our other business risk proxies. To capture the reaction of firm sales to economy-wide interest rate spreads, we employ three instruments, namely the standard deviation of the ratio debt in current liabilities to total assets, the standard deviation of interest expenses and the average growth of total assets. The first two variables are closely related to the debt capacity of the firm and thus should be related to the 'interest-part' of our risk proxy spread risk. However, to capture the impact of the 'sales-part' of this variable, we use average growth in assets bearing in mind that variation in sales must be picked up by total assets (i.e., the investment base of the company), which generate future sales. For income risk, which measures the reaction of firm profitability to changes in aggregated market sales, we use the standard deviation of the annual ratio of net income to firm sales as our instrument. Finally, for productivity risk, which captures changes in production efficiency, we use the standard deviation of the ratio of net income to average sales growth.

Turning from the economics of the instruments to the econometrics yields, that recent advancements in econometrics allow for sound instrument diagnostics testing for an instrument’s validity as well as its relevance. Many of these techniques were not available when previous studies were performed. Indeed, the only study employing IV estimates, by Chung (1989), includes three independent variables suffering from measurement error and three instruments. As we explain below, instrument tests are not possible here because this study aims to estimate an exactly identified system, making further specification tests impossible. Instead, based on the review of possible instruments shown in Appendix 3 and the economic reasoning presented above, we provide more instruments than key estimated independent variables, allowing thorough instrument diagnostics. Our approach is therefore in line with the recent request by Larcker and Rusticus (2009) that accounting research more thoroughly evaluate instruments. Consequently, we report our first-stage regression results for various IV estimators and the results of further related tests in Table 4.

----Please insert Table 4 approximately here----

As expected, the traditional two-stage least squares estimates (2SLS) and the results obtained using the generalized method of moments (GMM) estimator are very similar, as indicated in Table 4, Panel A. All proxies for intrinsic business risk besides productivity risk are statistically significant at the one-percent level, with point estimates ranging from 0.50 for growth risk to 0.75 for the income risk model (with inference based on Huber/White robust standard errors). In addition, the explanatory power of the income risk model, which closely resembles the specification of Mensah (1992), is driven by the accounting risk variable ln(income risk). In contrast, Mensah combines income risk and productivity risk into his term labeled 'adjusted accounting beta.' In other words, his specification forced the coefficient on income and productivity risk to be the same in the estimation. However, we find that removing this restriction creates a better specified model.

For the financial and operating risk variables, we encounter some remarkable differences between the two estimation techniques (2SLS vs. GMM). Recall that for exactly identified systems in which the number of endogenous variables equals the number of instruments, the results achieved using 2SLS and GMM coincide. This is not the case here, where we have an over-identified system with more potentially valid instruments than mis-measured variables. We use the efficient GMM estimator to explore this additional information via the optimal weighting matrix. Furthermore, the GMM coefficient estimates and statistics are robust to arbitrary heteroskedasticity. The previous literature sometimes reports difficulty predicting the sign for financial risk, but this issue may stem from the estimation technique employed (among other factors). Whereas financial risk in the growth and income risk models is either not significant (with coefficient estimates of 0.30) or is significant but with the opposite sign of that expected (-0.83), these problems do not arise when the GMM technique is used. In particular, the results for financial risk are positive and statistically significant in the growth risk model (coefficient estimate 0.48), and the results are not significantly different from zero in the income risk model (coefficient estimate -0.55). Finally, in comparing the OLS results (Table 3) with the IV results (Table 4), we recognize that all of our variables of interest (business risk, operating risk and financial risk) increase in absolute magnitude. For example, the coefficient of growth risk increases from 0.30 (OLS) to 0.50 (IV). This finding is consistent with our expectations and with standard knowledge indicating that OLS coefficient estimates are likely to be downward biased because of the measurement error (see Hausman 2001).

Turning to the question of non-nested model comparison, recall that the adjusted R-squared, although often reported by statistical packages, is not valid for instrumental variable estimates. Consequently, we report Pesaran and Smith's (1994) 'generalized R-squared' (Gen. R^2), offering a criterion for choosing between models estimated by the instrumental variable method. All three models are close in this respect: the Gen. R^2 is 0.34 if intrinsic business risk is measured by growth or income and productivity risk and 0.30 if spread risk is employed. However, these generalized R^2 values (unlike adjusted R^2 values based on OLS) do not account for the number of regressors used. Note that the number of independent variables differs in the growth and income risk specifications because of the inclusion of the additional parameter 'productivity risk' in the income risk model. Therefore, we also use Pesaran and Pesaran's (2009) 'generalized adjusted

R-squared' (Gen. Adj. R^2), which regards varying numbers of regressors, and determine that the highest Gen. Adj. R^2 is that of the growth risk model (0.34). We also use the 'generalized BIC' method, in line with Andrews and Lu (2001). This method provides us with a valid goodness of fit measure that considers the number of estimated coefficients used to determine the model fit. For each of the three models, Gen. BIC is calculated according to Gen. BIC = J – ln(N) * (M – P), where J is Hansen's J statistic, M the number of moments and P the number of model parameters. N is the number of observations. Consistent with our OLS evidence as presented in Table 3, the growth risk model again provides the best model fit (indicated by the smallest generalized BIC), followed by the income risk and spread risk models.

Overall, we conclude that, given the OLS and IV-GMM results from Table 3 and Table 4, the growth risk model performs best and significantly better than the spread risk model. In addition, although the differences between the growth and income risk models are not statistically significant, the evidence from the model selection criteria clearly favors the former model.

So far, we have conducted no extensive tests of instrument and econometric system specifications regarding identification. Information on this issue can be found in Table 4, panels B and D. We first turn to our first-stage regression results and instrument diagnostics as presented in Panel D. The key finding is that the model is well specified but suffers from weak instruments, and we address this problem by employing Fuller's (1977) maximum likelihood estimator being robust to this particular problem. As shown in Panel B, the coefficient estimates for intrinsic business risk vary in terms of their overall magnitudes: e.g., for the growth risk model, the coefficient estimates are 0.50 (GMM) and 0.57 (Fuller(1)). However, our overall conclusion remains valid. Specifically, the growth risk model is the favored model given the model selection criterion (BIC).

Because we are the first to present extensive instrument tests with reference to these research questions, we briefly summarize the main findings of our first-stage regression tests in Panel D. The aim is to determine if our instruments are relevant and valid. It is important to note that a first-stage regression is reported for each mis-measured independent variable. Turning to instrument relevance the overall model fit seems reasonable, with values of adj. R^2 mostly greater than 25%. Furthermore, the F-statistics of excluded instruments are statistically significant at the 1% level for all specifications. Thus, we can conclude that our instruments significantly help to explain the endogenous regressors. Since the partial R^2 of the excluded instruments from regressing the explanatory variable on the instrument vector is a useful measure of relevance in univariate models, as Shea (1997) points out, this can be misleading when there are multiple mis-measured variables. To address this potential concern, we also report Shea's partial R^2, a measure of instrument relevance for multivariate models that is suitable for use in our situation. Again, as in the case with the standard adjusted R^2, all values indicate relevant instruments. In summary, our instruments possess the relevance necessary for us to be confident that our above-described conclusions are valid.

In addition, we must test instrument validity as we strive for an identified system, i.e. a system that is neither over-identified nor under-identified. Whereas over-identification diagnostics have been available for a long time in econometrics (e.g., as presented for 2SLS by Sargan (1958) and for GMM by Hansen (1982)), under-identification tests have only been developed quite recently by Kleibergen and Paap (2006) and Kleibergen (2007). Over-identification tests such as the Sargan test or the Hansen J-statistic test analyze the null hypothesis that the instruments are valid. Thus, rejection of the null hypothesis will indicate problems with the estimated equations. Note that this poses no problems for our specification because we cannot reject the null hypothesis that the instruments are valid across all three models.[18] Under-identification relates to instrument relevance. Essentially, it tests whether the instruments are sufficiently correlated with the mis-measured regressors. Note that unlike in the over-identification test, the null hypothesis is that the system is under-identified. Because we reject the null hypothesis of under-identification, we conclude that our system is plagued by neither under- nor over-identification. Finally, we are left with the question of weak identification: i.e., the problem arising from a possible weak correlations between the instruments and the endogenous regressors. Weak instruments can lead to distorted estimates and problematic inferences, as explained in Stock and Yogo (2002, 2005). Stock and Yogo tabulate critical values for a test statistic (for i.i.d. errors, the Cragg-Donald statistic; for more general error structures, the Kleibergen-Paap statistic), indicating the bias and size problems arising from the weak instruments. Broadly speaking, weak instrument test statistics of less than 5 indicate potential problems of coefficient bias in the estimates. Being this the case, we employ the Fuller estimator, which is more robust to the weak instrument problem (e.g., Murray 2006, Andrews/Stock 2005). Our method of statistical inference is also robust to weak instruments, as shown by the Anderson-Rubin and Stock-Wright LM tests. Ultimately, based on our extensive discussion and instrument tests, we conclude that the growth risk specification performs best among the three models.

Our final step in this section is to employ the encompassing approach discussed by Verbeek (2000). Although growth risk seems best suited to capturing variations in market beta, it should encompass spread and income risk combined with productivity risk. Here under the encompassing approach is to be understood that all intrinsic business risk variables are in direct

[18] As outlined by Baum/Schaffer/Stillman (2007), the Sargan-Hansen test is a test of over-identifying restrictions. The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.

competition. Thus, we estimate an artificially nested model including all IBR variables. The OLS and IV regression results are presented in Table 5.

----Please insert Table 5 approximately here----

The OLS results clearly show that the spread risk variable is no longer statistically significant and that growth risk performs best. The results are even stronger for the IV regressions. Here, it appears that growth risk is the only intrinsic business risk proxy that is statistically significant in all specifications. We put more emphasis on the Fuller(4) estimates because this estimation technique is more robust to the weak instrument problem, which is relevant again.

Although we strongly recommend proper IV techniques for coping with problems arising from measurement error, it is worth acknowledging that only Chung (1989) recommends IV techniques as a first-order approach to addressing the errors-in-variables problem. The original studies by Mensah (1992) and Griffin/Dugan (2003) rely on a portfolio grouping approach, whereas Chung (1989) simply includes the grouping technique as a robustness test to underline his IV results. For this portfolio practice, the regressions are estimated on the portfolio level by first grouping on operating risk and afterwards the procedure is repeated with financial risk as the grouping variable. At last we would have to group the data based on the sorting according to one of our intrinsic business risk variables. However, this grouping approach entails many problems. For one, by definition, the sorting procedure is limited to sorting by one variable. Therefore, all three studies provide several grouping results; each time, a different variable is used to perform the grouping.[19] However, grouping based on only one variable, given that this

[19] In our case, we would have to group the data according to ten different independent variables and thirteen instruments. This would result in twenty-three varying results for each of the three competing models.

variable suffers from measurement error, means essentially grouping based on measurement error. Consequently, the results should be interpreted with caution at best, since estimates likely still suffer from bias. This problem is clearly noted in studies by Mandelker/Rhee (1984) and Chung (1989). In response, in both studies, the authors also sort using the instrumental variables instead of the independent variable, which mitigates the concern of biased coefficient estimates partially. Provided that the grouping method can be thought of simply as a special kind of IV estimation (Batistatou/McNamee 2008), we recommend to rely on proper instrumental variable techniques to cope with measurement error.

5. Further empirical analysis and robustness

The aim of this section is to provide further empirical analysis and test the robustness of our main findings: i.e., that growth risk is the most important and easily estimable intrinsic business risk factor and that we accept our first research hypothesis and reject the second one. Given these findings, one might object that our results are driven by the particular time period chosen; 1990-1999 was a time period of significant growth. To shed light on this issue, we re-estimate our specification for the main analysis for various time periods. In particular, we report the OLS and instrumental variable results (Fuller(4)) for the time periods of 1980-1989, 1985-1994, and 1995-2004.

----Please insert Table 6 approximately here----

Our main findings remain valid. Panel A of Table 6 presents the results indicating that growth risk is the most appropriate proxy for business risk for all periods. Furthermore, the instrumental variable estimates show that all specifications suffer from weak instruments and thus that the use of Fuller's estimator is appropriate.

Prior research shows that cost of equity estimates differ across industries (Fama/French 1992), leading to terms of industry costs of equity (Easton/Monahan 2005). Consequently, we re-estimate the above specifications, but we additionally include industry indicator variables in all of our regressions[20]. Table 6, Panels B and C, presents the OLS and IV estimates for the time period of 1990-1999 based on net income from operations accounting flow. In addition, Table 6, Panel D, provides the first-stage regression results, which show that weak instruments are again a

[20] Note that we include 11 industry indicator variables because we drop financial firms from our sample. The industry classifications are obtained from Kenneth French's website, available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

concern. Consequently, we focus on the estimates given by the Fuller method. Notably, only if intrinsic business risk is measured using growth risk does the significantly positive relation between systematic risk and intrinsic business risk remain valid.

Regarding the main finding that spread risk is outperformed by growth risk, we acknowledge that this finding could be due to the chosen market interest rate spread: i.e., the difference between the returns on long-term government bonds and one-month Treasury bills[21]. Because this interest spread choice mainly affects the estimation of spread risk, we calculate various interest spreads recommended in the prior literature and re-estimate our model specifications. First, we calculate the ex post real interest factor[22] as the difference between the 3-month TBill return at time t-1 and the inflation rate at time t[23].

----Please insert Table 7 approximately here----

Table 7, Panels A and B, presents the OLS and IV estimates for this modified spread risk specification, whereas Panel C sums up the first-stage regression results. Our results indicate that our main findings remain valid. Hereafter we use the differences between the long-term corporate and long-term government bond returns as a market interest rate spread. In particular, we use the spreads of Aaa and Baa-rated long-term bond returns and 10-year government bonds[24] and re-estimate our three competing models. The findings (results not tabulated) indicate that the growth risk model still performs best, followed by the income risk model.

[21] See Section 3, and see Chen/Roll/Ross (1986) and Fama/French (1993) for further reading.

[22] See Chen/Roll/Ross (1986).

[23] The data on TBill returns are provided by the H.15 Federal Reserve Statistical Release; the data for inflation rates are published by the Bureau of Labor Statistics.

[24] All data are provided by the H.15 Federal Reserve Statistical Release.

In addition, we wish to test if the decomposition of growth risk into income and productivity risk is worthwhile. So far, our results have been based on the NIOP accounting flow which captures firm profitability better compared to reported net incomes. As suggested in the previous literature, we employ two more cash-flow like accounting cash-flows to reduce distortion based on the use of differing accounting practices (Ismail/Kim 1989, Mensah 1992). These variables then successively replace net income from operations and therefore mainly affect our income risk proxy, which is defined as the risk associated with the covariance of a firm's net income from operations and market-wide sales. The first variable adds depreciation back into net income from operations and is labeled 'fund flow from operations' (FFOP = (IBADJ+DP)/(CSHPRI·AJEX)). The second variable, 'working capital from operations,' also corrects for the effect of taxes by adding deferred income taxes as follows: WCOP=(IBADJ+DP+TXDI)/(CSHPRI·AJEX). Then we re-estimate our previous specifications using these two accounting flow variables instead of net income from operations.

The results reported in Table 7, Panels D and E, present information consistent with our main analysis. The growth risk specification performs significantly better than the spread risk specification does. Adj. R^2 and BIC (when OLS is used) and generalized R^2 and generalized BIC (when IV estimates are used) indicate that intrinsic business risk is most appropriately captured by growth risk. Still, the income risk model does not outperform growth risk. We also re-estimate all specifications for 3 different time periods (1980-1989, 1985-1994, 1995-2004) based on FFOP and WCOP (results not tabulated) and find the same pattern.

So far, we have stressed various 10-year time spans and estimation methods that mainly affect the estimation results for spread, income and productivity risk. This approach has helped us to further establish the importance of our preferred business risk proxy, growth risk. Turning to the dependent variable in our regression models, we now point to prior literature suggesting competing estimation methods for CAPM market beta (e.g., Shanken 1992). Regarding the recent estimation adjustments recommended by Levy and Roll (2010), the authors find that our conventional market beta proxy is consistent with the theoretical CAPM. Thus, we do not employ different methods to determine our market beta proxy. However, in contrast to differing estimation procedures the extant literature also concludes that a 5-year time span (rather than a 10-year time span) is another reasonable time span for market beta estimation (Groenewold/Fraser 2000). We also check robustness using this time span as the estimation period for all model variables. Given a correlation of 88% between the market betas obtained using these two time spans, the results unsurprisingly remain the same.

Lastly, we would like to point out that a mis-measured right-hand variable (e.g., growth risk) makes it necessary to use the IV method, whereas a mis-measured left-hand variable does not cause a downward bias (Hausman 2001). The only result will be less precision in the estimated coefficients, which will make it more challenging to obtain significant results. Being this the case, the performance of the growth risk model actually improves.

6. Conclusion and discussion

This study examines the determinants of the CAPM market beta. Consistent with prior literature, we consider these key determinants to be operating and financial leverage and intrinsic business risk. However, economic research employs various proxies for intrinsic business risk and uses different econometric techniques and research designs to establish that intrinsic business risk (however specified) is the key determinant of the cost of equity capital. In particular, competing empirical proxies recommended are growth risk and macroeconomic risk measured by interest rate spreads. Another strand of literature claims that it is necessary to decompose growth risk into factors capturing firm profitability and efficiency. The natural question arises of whether all of these constructs are equally valid? It remained unclear when the present research was first undertaken whether they could all explain variation in the cost of equity capital estimates equally well and whether they were significantly positively correlated with the CAPM beta. Finally, because all specifications require estimated independent variables, instrumental variable estimators must be used to address the issue of measurement error. Given the recent advances in the econometrics literature, the aim of this research is to shed more light on these estimation techniques and their impact on the results reported so far.

To answer these questions, we first provide a comprehensive decomposition approach, which is powerful enough to nest models proposed in the prior literature. This puts competing specifications on a level playing field and is a necessary step to make cross-model comparisons possible. After establishing this approach, we test three competing proxies of intrinsic business risk proxies. Our main finding is that the most appropriate intrinsic business risk proxy is growth risk, which is given by the covariance of changes in firm sales with changes in market-wide sales. growth risk clearly outperforms business risk, as measured by the reactions of firm sales to macroeconomic interest rate spreads. We also decompose growth risk into factors capturing firm profitability and efficiency, but this step does not yield a model with superior fit.

Furthermore, we show that the estimated specifications that try to mitigate the effect of measurement error using instrumental variable techniques suffer from weak instruments. By employing estimators, which are more robust to this particular problem, we confirm the strength of the growth risk model. Thus, we can conclude that this key accounting figure plays a crucial role as a determinant of market beta.

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Appendix 1

Data requirements for the model specification based on the

'Net income from operations' (NIOP) Accounting Flow

We obtain the following items from COMPUSTAT:

Data item number	**Item Name**	**Description**
#6	AT	total assets (mm$)
#8	PPEQT	property, plants and equipment – total (net) (mm$)
#9	DLTT	long-term debt - total (mm$)
#11	CEQT	common equity - tangible (mm$)
#12	SALE	sales (net) (mm$)
#15	XINT	interest expenses (mm$)
#19	DVP	dividends - preferred (mm$)
#20	IBADJ	income before extra items - adjusted for common stock equivalents (mm$)
#27	AJEX	adjustment factor (cum.) by ex-date
#34	DLC	debt in current liabilities (mm$)
#54	CSHPRI	common shares for basic eps (mm)
#60	CEQ	common equity - total (mm$)

Notes:
We obtain annual data during the period from 1990 to 1999 for these Compustat items.

We obtain the following items from the Center for Research in Security Prices (CRSP):

Item Name	**Description**
RET	returns – incl. dividends
VWRETD	value-weighted returns - incl. dividends
SHROUT	shares outstanding
PRC	price or bid/ask average

Notes:
We obtain monthly data from CRSP. We require firms to have a minimum of 60 observations for the period from 1990 to 1999.

Appendix 2

Calculation of Accounting Flows

The following table reports the formulas for our four employed accounting flows[25]. Detailed data requirements for our preferred formula, 'net income from operations' (NIOP), are given in Appendix 1 for firms with and without financial leverage. Throughout the analysis we also employ 'fund flows from operations' (FFOP), 'working capital from operations' (WCOP) and 'cash flow from operations' (CFOP).

We calculate each accounting flow using firm-level data from 1990 to 1999 as follows:

NIOP_l	=	IBADJ / (CSHPRI · AJEX)
NIOP_u	=	(IBADJ + DVP + (1 – TAX) · XINT) / (CHSPRI · AJEX)
FFOP_l	=	(IBADJ + DP) / (CSHPRI · AJEX)
FFOP_u	=	(IBADJ + DP + DVP + (1-TAX) · XINT) / (CSHPRI · AJEX)
WCOP_l	=	(IBADJ + DP + TXDI) / (CSHPRI · AJEX)
WCOP_u	=	(IBADJ + DP + TXDI + DVP + (1-TAX) · XINT) / (CSHPRI · AJEX)
CFOP_l	=	((IBADJ + DP + TXDI) - (ACT – CHE - LCT) + (L1.ACT - L1.CHE - L1.LCT)) / (CSHPRI · AJEX)
CFOP_u	=	((IBADJ + DP + TXDI + DVP + (1-TAX) · XINT) - (ACT – CHE - LCT) + (L1.ACT - L1.CHE - L1.LCT)) / (CSHPRI · AJEX)

Notes:

The subscripts 'l' and 'u' refer to a firm with and without financial leverage, respectively. 'TAX' accounts for the tax rate. We set TAX to 0.4. Our results are robust to a wide range of variations in 'TAX'.

We list the description of the variables used for NIOP in Appendix 1. For the other three accounting flows, we also require non-missing financial statement data for 'depreciation and amortization' ('DP'), 'income taxes-deferred' ('TXDI'), 'current assets-total' ('ACT'), 'cash and short-term investments' ('CHE') and 'current liabilities-total' ('LCT'). The operator 'L1' is the lag operator. These additional data requirements create differing numbers of observations, as presented in Table 6. Our results are robust if the data for all accounting flows are required simultaneously.

[25] See also Ismail/Kim (1989) and Mensah (1992).

Appendix 3

Instrument Definition

Since the independent variables of our models are not observable and must be estimated first, creating measurement error, we use the instrumental variable approach to reduce the potential bias in the OLS regressions. We use the following instruments for each variable:

Label	Definition	Source
IV growth risk (1)	= Standard deviation of sales	Chung (1989)
IV growth risk (2)	= Average growth of total assets	Beaver/Kettler /Scholes (1970)
IV spread risk (1)	= Standard deviation of the ratio of debt in current liabilities to total assets	*
IV spread risk (2)	= Standard deviation of interest expenses	*
IV spread risk (3)	= Average growth of total assets	*
IV income risk (1)	= Standard deviation of the ratio of net income to sales	*
IV productivity risk (1)	= Standard deviation of the ratio of net income to average sales growth	*
IV operating risk (1)	= Average of the ratio of property, plant and equipment to total assets	Mandelker/Rhee (1984)
IV operating risk (2)	= Standard deviation of net income	Chung (1989)
IV financial risk (1)	= Average ratio of total long-term debt to total assets	Mandelker/Rhee (1984)
IV financial risk (2)	= Average ratio of interest expenses to operating income after depreciation	Chung (1989)
IV financial risk (3)	= Average ratio of total long-term debt to common tangible equity	Chung (1989)
IV financial risk (4)	= Average of the ratio of total long-term debt to total common equity	Chung (1989)

Notes:
This table states the definitions of the instruments used. The abbreviation “IV” stands for ‘instrumental variable’. The instruments are computed on a firm-level basis using annual data from 1990 to 1999. Most estimated risk proxies are instrumented using more than one instrument. We therefore show the number of each instrument belonging to the risk proxy of interest. The ‘Definition’ column specifies how we calculated each instrument. The ‘Source’ column states each instrument's original use in the related literature. The instruments labeled ‘*’ are newly proposed in this study based on the reasoning provided in the main text.

Appendix 4

Vuong's (1989) test of overlapping models

Vuong (1989) provides a likelihood ratio test for model selection that is helpful to us as we seek to address our research question regarding which model is best suited to explaining variations in market beta. It tests the null hypothesis that two models are equally close to explaining the 'true data generating process' (dgp) against the alternative that one model is closer.

Competing models are overlapping if their intersection does not equal the null set and neither model is a subset of the other one. Because our models of interest (i.e., the growth, spread and income risk models) contain financial and operating risk as well as the income to equity ratio as common independent variables but vary in terms of the variable that they use for intrinsic business risk, it is necessary to address the issue of model overlap.

Since the intersection of these theoretical models is not empty, it is not a priori clear whether or not $f(\cdot) = g(\cdot)$, where f and g denote the density functions for the first and the second models to be compared, respectively (e.g., the growth and spread risk models). We must first test whether both densities are distinct before we are able to use Vuong's model selection test. For example, consider the simplified case in which the true dgp is driven only by financial risk and not by any proxy of intrinsic business risk. Adding growth risk to one model and spread risk to the other would actually cause nuisance due to the misspecification of both models. The Vuong test could favor one model, although both comprise the empirical specification of financial risk and therefore are equally suited to capturing the true dgp. Thus, it is essential to discriminate between the overlapping models and test if they differ sufficiently in their intrinsic business risk variable before using the Vuong test.

Vuong proposes the following test statistic:

$$H_0^w : w_*^2 = Var_0\left[\ln\frac{f(y\,|\,x,\theta_*)}{g(y\,|\,x,\gamma_*)}\right] = 0$$

where the variance with respect to the true dgp, $f(y\,|\,x,\theta_*)$, represents the first model's conditional density function (e.g., that of the growth risk model) and where $g(y\,|\,x,\gamma_*)$ represents the second model's conditional density (e.g., the spread risk model's density in this case). y and x refer to the dependent and independent variables, respectively. θ_* and γ_* are the pseudo-true values for θ and γ where the likelihood function for the true dgp takes a maximum. $\hat{\theta}$ and $\hat{\lambda}$ are the maximum likelihood estimators of θ_* and γ_*.

Vuong proves that variance w_*^2 equals zero if and only if $f(\cdot) = g(\cdot)$. Therefore, we first compute the estimate $\widehat{w}^2$ of w_*^2 as follows:

$$\widehat{w}^2 = \frac{1}{N}\sum_{i=1}^{N}\left(\ln\frac{f\left(y_i\,|\,x_i,\hat{\theta}\right)}{g\left(y_i\,|\,x_i,\hat{\gamma}\right)}\right)^2 - \left(\frac{1}{N}\sum_{i=1}^{N}\ln\frac{f\left(y_i\,|\,x_i,\hat{\theta}\right)}{g\left(y_i\,|\,x_i,\hat{\gamma}\right)}\right)^2.$$

Because the ordinary least squares method assumes normally distributed error terms, we attain

$$\ln\left(f\left(y\,|\,x,\hat{\theta}\right)\right) = -\ln\left(\sqrt{2\pi\widehat{\sigma_f^2}}\right) - \frac{\left(y-\widehat{y_f}\right)^2}{2\widehat{\sigma_f^2}},$$

where $\widehat{\sigma}_f^2$ is the sum of squared residuals divided by N and $\hat{y}_f$ is the linear prediction for the first model. The formulas are the same for the second model. The first summand of $\widehat{w}^2$ can easily be computed. For the second summand, we calculate the difference between the log likelihoods. Vuong proves that under $H_0^w : w_*^2 = 0$, the following holds in distribution:

$$N\widehat{w}^2 \xrightarrow{d} M_{p+q}(\lambda_*),$$

where p and q are the dimensions of θ and γ (5 for the growth and spread risk model and 6 for the income risk model). $M_{p+q}(\lambda_*)$ denotes the cumulative density function of the weighted sum of the chi-squared variables $\sum_{j=1}^{p+q} \lambda_* Z_j^2$. The Z_j^2 are i.i.d. $\chi^2(1)$, and λ_{*j} represents the eigenvalues of the $(p+q)\times(p+q)$ matrix

$$W = \begin{pmatrix} -B_f(\theta_*)A_f(\theta_*)^{-1} & -B_{fg}(\theta_*,\gamma_*)A_g(\gamma_*)^{-1} \\ -B_{gf}(\gamma_*,\theta_*)A_f(\theta_*)^{-1} & -B_g(\gamma_*)A_g(\gamma_*)^{-1} \end{pmatrix},$$

where $A_f(\theta_*) = E_0\left[\partial^2 \ln f/\partial\theta\partial\theta'\right]$, $B_f(\theta_*) = E_0\left[(\partial \ln f/\partial\theta)\left(\partial \ln f/\partial\theta'\right)\right]$, and the matrices $A_g(\gamma_*)$ and $B_g(\gamma_*)$ are similarly defined for density $g(\cdot)$; the cross-matrix is $B_{fg}(\theta_*,\gamma_*) = E_0\left[(\partial \ln f/\partial\theta)\left(\partial \ln g/\partial\gamma'\right)\right]$ and the expectation is with respect to the true dgp.

Cameron and Trivedi (2005) illustrate how to calculate theses matrices. $A_f\left(\hat{\theta}\right)$ and $A_g\left(\hat{\gamma}\right)$ are the inverses of the usual maximum likelihood variance matrix for each empirical model. To calculate $B_f\left(\hat{\theta}\right)$, we estimate the first model using robust standard errors. Afterwards, the robust maximum likelihood matrix of $B_f\left(\hat{\theta}\right)$ is multiplied by $A_f\left(\hat{\theta}\right)$ on the left- and the right-hand sides and divided by N. The same holds for the calculation of $B_g\left(\hat{\gamma}\right)$. Last, we apply $B_{fg}\left(\widehat{\theta_*},\widehat{\gamma_*}\right) = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widehat{\mu_{fi}}\right)x_i \times \left(y_i - \widehat{\mu_{gi}}\right)x_{gi}'$.

The hypothesis H_0^w is rejected at level α if $N\hat{w}^2$ exceeds the upper α percentile of the $M_{p+q}\left(\hat{\lambda}\right)$ distribution using the eigenvalues $\hat{\lambda}_j$ of the sample analogue of W. In a simulation, we generate an empirical distribution for $M_{p+q}(\lambda_*)$ using the calculated eigenvalues and ten iid

$\chi^2(1)$ variables (recall that $p=q=5$ for the growth and spread risk models). If H_0^w is not rejected, it is impossible to discriminate between the two models given the data. If H_0^w is rejected, both models are statistically distinct from the intrinsic business risk variable that they employ. If this is the case, we use the usual Vuong (1989) model selection test, as detailed in the strictly nonnested case, based on the likelihood ratio statistic:

$$LR\left(\hat{\theta},\hat{\gamma}\right)=LR^f\left(\hat{\theta}\right)-LR^g\left(\hat{\gamma}\right)=\sum_{i=1}^{N}\ln\frac{f\left(y\mid x,\hat{\theta}\right)}{g\left(y\mid x,\hat{\gamma}\right)}$$

and test H_0^w against H_f or H_g using the following feature:

$$T_{LR}=\frac{1}{\sqrt{N}}\frac{LR\left(\hat{\theta},\hat{\gamma}\right)}{\hat{w}}\xrightarrow{d}N\left(0,1\right).$$

If the Vuong test favors one model and both models can be discriminated, the better model fit will only be due to the leading model's variable for intrinsic business risk.

Table 1
Summary Statistics

Industry	Industry Name	N		growth risk	spread risk	income risk	productivity risk	Market risk	operating risk	financial risk	income to Equity
1	**Consumer NonDurables**	22	Mean	2.2008	0.0251	2.8779	0.3878	0.7824	1.3045	1.1071	0.0013
	(Food, Tobacco, Textiles, Apparel, Leather, Toys)		Median	1.7633	0.0216	3.1700	0.3889	0.7316	1.1802	1.0378	0.0006
2	**Consumer Durables**	18	Mean	3.4415	0.0427	4.6935	0.5550	0.7986	1.3237	1.1387	0.0019
	(Cars, TV's, Furniture, Household Appliances)		Median	3.3247	0.0334	4.4281	0.4954	0.7513	1.2497	1.0597	0.0016
3	**Manufacturing**	35	Mean	2.6023	0.0276	4.5964	0.4724	0.8587	1.5570	1.3088	0.0030
	(Machinery, Trucks, Planes, Off Furn, Paper)		Median	2.8434	0.0267	3.6214	0.3947	0.8634	1.3275	1.1612	0.0016
4	**Oil, Gas, and Coal Extraction and Products**	8	Mean	3.8265	0.0367	3.2263	0.3804	0.8129	1.1554	1.3661	0.0015
			Median	3.4160	0.0419	3.0726	0.2763	0.7662	0.6482	1.3908	0.0007
5	**Chemicals and Allied Products**	9	Mean	1.8871	0.0424	2.4087	0.3444	0.9747	1.1474	1.0992	0.0043
			Median	1.5766	0.0258	2.1893	0.2332	0.8718	0.9321	1.1097	0.0010
6	**Business Equipment**	15	Mean	4.8703	0.0473	5.8081	0.6628	1.1596	1.1983	1.1034	0.0048
	(Computers, Software, and Electronic Equipment)		Median	4.7765	0.0355	5.1744	0.6472	1.0947	1.1027	1.0699	0.0012
7	**Telephone and Television Transmission**	1	Mean	3.9118	0.0191	6.3247	0.4065	1.4497	1.5505	1.0227	0.0032
			Median	3.9118	0.0191	6.3247	0.4065	1.4497	1.5505	1.0227	0.0032
8	**Utilities**	32	Mean	1.3788	0.0191	1.3308	0.5627	0.3263	0.5753	1.5946	0.0026
			Median	1.1853	0.0157	1.3214	0.4916	0.3382	0.4739	1.3534	0.0014
9	**Wholesale, Retail, and Some Services**	38	Mean	3.8925	0.0304	4.1760	0.6632	0.9364	1.0357	1.1477	0.0030
	(Laundries, Repair Shops)		Median	3.2271	0.0230	3.4221	0.6670	0.9005	0.9534	1.0767	0.0006
10	**Healthcare, Medical Equipment, and Drugs**	14	Mean	4.3484	0.0532	4.1006	0.6291	1.0136	1.0654	1.0267	0.0009
			Median	4.4521	0.0336	3.8038	0.5968	0.9695	1.0791	1.0140	0.0002
12	**Other**	20	Mean	4.5969	0.0386	4.6116	0.7201	1.0896	0.8375	1.1982	0.0017
	(Mines, Constr, BldMt, Trans, Hotels, Bus Serv)		Median	4.5782	0.0275	4.2516	0.5481	1.0903	0.8047	1.0892	0.0011

Notes

This table reports summary statistics of estimated risk proxies for 212 firms from 1990 to 1999. Each firm is assigned to one of Fama and French's 12 industry classification (excluding financial firms). 'N' reports the number of firms per industry. The following risk proxies are reported: 'growth risk' is the reaction of firm sales to changes in aggregated market sales, 'spread risk' is the percentage change of firm sales to a percentage change in a market wide interest shock, 'income risk' is the reaction of firm net income to changes in aggregated market sales. 'productivity risk' is the percentage change of firm sales to a percentage change of net income. 'Market risk' is the CAPM beta. 'operating risk' is the percentage change of operating income associated with a given percentage change in firm sales. 'financial risk' represents the percentage change of net income associated with a given percentage change in operating income. 'income to Equity' is the average ratio of net income to equity market value of each firm during the sample period. All variables are estimated and defined as described in 3. Data and Estimation Procedure.

Table 2

Correlation Table

Panel A: Estimated variables

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1 growth risk	1							
2 spread risk	0.46	1						
3 income risk	0.50	0.17	1					
4 productivity risk	0.45	0.12	-0.04	1				
5 Market risk	0.53	0.25	0.50	0.07	1			
6 financial risk	-0.24	-0.04	0.03	-0.33	-0.22	1		
7 operating risk	-0.22	-0.19	0.46	-0.37	0.13	-0.06	1	
8 income to Equity	0.04	0.05	-0.02	-0.02	-0.11	0.06	-0.03	1

Notes:

This table provides pairwise correlations of the estimated variables. ‘growth risk’ (‘$Grrisk_i$‘: The reaction of firm sales to changes in aggregated market sales), ‘spread risk’ (‘$Sprisk_i$’: The percentage change of firm sales to a percentage change in a market wide interest shock), ‘income risk’ (‘$Inrisk_i$’: The reaction of firm net income to changes in aggregated market sales) and ‘productivity risk’ (‘$Prodrisk_i$’: The percentage change of firm sales to a percentage change of net income) are the risk proxies of interest according to our model comparison. ‘Market risk’ is the CAPM market beta and in all regressions the dependent variable. ‘operating risk’ (‘$Oprisk_i$’) is the percentage change of operating income that is associated with a given percentage change in firm sales. ‘financial risk’ (‘$Finrisk_i$’) represents the percentage change of net income that is associated with a given percentage change in operating income. ‘income to Equity’ (‘$income\_to\_Equity_i$’) is the average ratio of net income to equity market value of each firm during the sample period. All variables are estimated as described in 3. Data and Estimation Procedure. Correlation coefficients larger than the absolute value of 0.11 are significant at the 10% level.

(continued)

Table 2 *(Continued)*

Panel B: Instruments for growth-, spread-, income-, productivity-, operating- and financial risk

No	Name	Calculation	1	2	3	4	5	6	7	8	9	10	11	12	13
1	IV growth risk (1)	sd(sales)	1												
2	IV growth risk (2)	mean(assetgrowth)	0.85	1											
3	IV spread risk (1)	sd(dlc/at)	-0.14	-0.18	1										
4	IV spread risk (2)	sd(xint)	0.66	0.79	-0.19	1									
5	IV spread risk (3)	mean(assetgrowth)	0.85	1.00	-0.18	0.79	1								
6	IV income risk (1)	sd(ni/sales)	-0.37	-0.36	-0.01	-0.34	-0.36	1							
7	IV productivity risk (1)	sd(ni/sales_growth)	0.04	0.01	-0.10	0.01	0.01	0.16	1						
8	IV financial risk (1)	mean(dltt/at)	-0.07	-0.01	-0.16	0.18	-0.01	0.02	0.02	1					
9	IV financial risk (2)	mean(xint/oiadp)	0.67	0.69	-0.21	0.72	0.69	-0.38	0.07	0.19	1				
10	IV financial risk (3)	mean(dltt/ceqt)	0.07	0.10	-0.10	0.34	0.10	-0.12	0.06	0.79	0.28	1			
11	IV financial risk (4)	mean(dltt/ceq)	-0.00	0.06	-0.12	0.31	0.06	-0.07	-0.01	0.92	0.27	0.86	1		
12	IV operating risk (1)	mean(ppeqt/at)	-0.20	-0.07	-0.12	0.01	-0.07	0.10	-0.05	0.40	-0.00	0.12	0.35	1	
13	IV operating risk (2)	sd(ni)	0.15	0.17	-0.09	0.18	0.17	0.11	0.31	0.00	-0.03	0.05	-0.03	0.04	1

Notes:

This table provides pairwise correlations of the instruments. The first column states the instruments' name, the second column specifies its calculation. Instruments 1 to 7 differ across our three model comparisons. 'growth risk' ('$Grrisk_i$') is instrumented using two instruments: 'IV growth risk(1)' is the standard deviation of sales. 'IV growth risk(2)' is the average growth of total assets during the sample period. 'spread risk' ('$Sprisk_i$') is instrumented using 'IV spread risk(1)': The standard deviation of the ratio debt in current liabilities to total assets; 'IV spread risk(2)': The standard deviation of interest expenses and 'IV spread risk(3)': The average growth of total assets. The instrument for 'income risk' ('$Inrisk_i$') is 'IV income risk(1)': The standard deviation of the ratio net income to sales. Common risk factors for all three models are 'operating risk' ('$Oprisk_i$') and 'financial risk' ('$Finrisk_i$'). Their instruments are: 'IV operating risk(1)': The average of the ratio property, plant and equipment to total assets; 'IV operating risk(2)': The standard deviation of net income; 'IV financial risk(1)': The average of the ratio total long term debt to total assets; 'IV financial risk(2)': Average of the ratio interest expenses to operating income after depreciation; 'IV financial risk(3)': Average of the ratio total long term debt to common equity tangible; 'IV financial risk(4)': Average of the ratio total long term debt to total common equity. The variable 'productivity risk' ('$Prodrisk_i$') is only used in the 'income risk model'. Its instrument 'IV productivity risk(1)' is the standard deviation of the ratio of net income to average sales growth. All variables are estimated as described in 3. Data and Estimation Procedure.

Correlation coefficients larger than the absolute value of 0.11 are significant at the 10% level.

Table 3

OLS Regression Results for 212 firms

	Exp. Sign	growth risk model (1)	spread risk model (2)	income risk model (3)	restricted model (a)	restricted model (b)
ln(growth risk)	+	0.30***				
ln(spread risk)	+		0.14***			
ln(income risk)	+			0.33***		
ln(productivity risk)	-/+			-0.08*	0.03	
ln(financial risk)	+	-0.09	-0.33***	-0.51***	-0.32*	-0.37***
ln(operating risk)	+	0.24***	0.24***	-0.05	0.21***	0.20***
ln(income_to_Equity)	-	-0.09***	-0.09***	-0.07***	-0.09***	-0.09***
Cons		-1.13***	-0.34*	-1.16***	-0.81***	-0.83***
Adj. R^2		0.39	0.26	0.33	0.19	0.19
BIC		250.36	292.97	274.42	311.40	306.66
F-Statistic		29.24***	20.38***	19.96***	15.56***	18.60***
N		212	212	212	212	212
Wald Test (risk models (1), (2), (3) compared to restricted model (b)						
(p-val)		(0.00)	(0.00)	(0.00)		
Model Selection:						
Vuong-Test						
model (1) compared to (2) and (3):						
model discrimination test, Stat.			57.15***	51.93***		
Selection test, Z-Stat			2.82***	1.67*		
BIC-Discrimination-Test						
model (1) compared to (2) and (3):						
t-Stat.			-21.43***	-8.54***		

Notes:

This table presents OLS regression estimates of the determinants of market beta. The dependent variable in each model is the natural logarithm of firm i's market beta (β_i). We estimate five different models, namely the 'growth risk model', the 'spread risk model' and the 'income risk model', which are the three models of interest regarding our model comparison. Furthermore, we estimate two restricted models ((a), (b)), which suppress the variables 'ln(growth risk)', 'ln(spread risk)' and 'ln(income risk)'. 'restricted model(b)' differs from 'restricted model(a)' in the use of the variable 'ln(productivity risk)'.

For each variable the expected coefficient sign is reported. We report Adjusted-R^2 ('Adj.-R^2'), the Bayesian Information Criterion ('BIC') and the F-Statistic measuring the significance of the overall model. 'N' is the number of observations. Using the Wald-coefficient test of equality we exhibit evidence that adding the logarithm of growth risk, spread risk and income risk significantly increases the regression model's Adj.-R^2 (see reported p-values). We also apply the Vuong Test to determine whether the Adj.-R^2 of one estimated model is significantly larger than another. First we estimate Vuong's (1989) discrimination test for overlapping models and afterwards report the Vuong Z-statistic (see Appendix 4 for details). Further we implement a BIC discrimination test according to Augustin/Sauerbrei/Schumacher (2005) and Buckland/Burnham/Augustin (1997). Using bootstrap methods we generate an empirical distribution of each model's BIC and test the null hypothesis H0: BIC of model (1) greater or equal BIC of model (2) and (3) respectively. We report the t-Statistic.

'***' denotes the significance at the 1% level, '**' refers to the significance at the 5% level and '*' to the 10% level significance. All variables are estimated and defined as described in 3. Data and Estimation Procedure.

Table 4

Instrumental Variable Regression Results for 212 firms, 1990-1999

Panel A: Two stage least squares (2SLS) and Generalized Method of Moments (GMM two stage)

		2SLS			GMM2s		
	Exp. Sign	growth risk model (1)	spread risk model (2)	income risk model (3)	growth risk model (1)	spread risk model (2)	income risk model (3)
ln(growth risk)	+	0.50***			0.50***		
ln(spread risk)	+		0.49***			0.42***	
ln(income risk)	+			0.75***			0.80***
ln(productivity risk)	-/+			-0.15			-0.09
ln(financial risk)	+	0.30	-0.26	-0.83*	0.48*	-0.23	-0.55
ln(operating risk)	+	0.45***	0.41***	-0.20	0.50***	0.43***	-0.21
ln(income_to_Equity)	-	-0.08***	-0.10***	-0.05**	-0.09***	-0.09***	-0.06***
Cons		-1.33***	0.96*	-1.44***	-1.46***	0.78*	-1.61***

Panel B: Fuller(1) and Fuller(4)

		Fuller(1)			Fuller(4)		
	Exp. Sign	growth risk model (1)	spread risk model (2)	income risk model (3)	growth risk model (1)	spread risk model (2)	income risk model (3)
ln(growth risk)	+	0.57***			0.54***		
ln(spread risk)	+		0.72**			0.58***	
ln(income risk)	+			0.99**			0.82***
ln(productivity risk)	-/+			-0.10			-0.14
ln(financial risk)	+	0.52	-0.02	-0.69	0.43	-0.17	-0.80
ln(operating risk)	+	0.49***	0.39**	-0.39	0.48***	0.41***	-0.26
ln(income_to_Equity)	-	-0.08***	-0.11***	-0.04	-0.08***	-0.10***	-0.05*
Cons		-1.44***	1.73*	-1.66***	-1.40***	1.27*	-1.51***

Panel C: Model Selection

	growth risk model (1)	spread risk model (2)	income risk model (3)
Gen. R^2	0.34	0.30	0.34
Gen. Adj. R^2	0.33	0.29	0.32
Gen. BIC	-19.31	-12.74	-15.21
Gen. BIC-Discrimination-Test			
model (1) compared to (2) and (3):			
t-Stat.		-9.24***	-5.57***
N	212	212	212

Notes:

Panel A presents two-stage-least-squares (2SLS) and Generalized Method of Moments (gmm2s) instrumental variable regression results of the determinants of 'Market Beta'. Panel B presents Fuller(1) and Fuller(4) estimates of the same models appropriate in the case of weak instruments. For 2SLS, Fuller(1) and Fuller(4) are the estimates efficient for homoscedasticity only and statistics are robust to heteroscedasticity. For the GMM2s estimation are the estimates efficient for arbitrary heteroscedasticity and statistics robust to heteroscedasticity. Panel C presents IV model selection criteria. The dependent variable in each model is the natural logarithm of firm i's 'Market Beta' ('β_i').

We estimate three different models using the instrumental variable technique, namely the 'growth risk model', the 'spread risk model' and the 'income risk model': 'growth risk' is instrumented by the standard deviation of sales ('IV growth risk(1)') and the average growth of total assets ('IV growth risk(2)'). 'spread risk' is instrumented by standard deviation of the ratio debt in current liabilities to total assets ('IV spread risk(1)'), the standard deviation of interest expenses ('IV spread risk(2)') and the average growth of total assets ('IV spread risk(3)'). 'income risk' is instrumented by the standard deviation of the ratio net income to sales ('IV income risk(1)'). The variable 'productivity risk' is instrumented by the standard deviation of the ratio net income to average sales growth ('IV productivity risk(1)'). 'operating risk' is instrumented by the average of the ratio property, plant and equipment to total assets ('IV operating risk(1)') and the standard deviation of net income ('IV operating risk(2)'). Finally 'financial risk' is instrumented by the average of the ratio total long term debt to total assets ('IV financial risk(1)'), the average of the ratio interest expenses to operating income after depreciation ('IV financial risk(2)'), the average of the ratio total long term debt to common equity tangible ('IV financial risk(3)') and the average of the ratio total long term debt to total common equity ('IV financial risk(4)'). The variable 'income_to_Equity' is not instrumented since measured error is negligible.

We report the Pesaran/Smith's (1994) 'Generalized-R^2 ('Gen.-R^2') offering a model selection criterion for choosing between models estimated by the instrumental variable method. This Generalized-R^2 does not account for the number of regressors used. Therefore we additionally employ Pesaran/Pesaran's (2009) 'Generalized-Adjusted-R^2 ('Gen.Adj.R^2') being suited for IV estimation and taking the number of regressors into account.

Further we implement 'Generalized BIC' (see Andrews/Lu 2001, p.125) providing a valid goodness of fit measure for the overall model. For each of the three models 'Gen. BIC' is calculated according to: 'Gen. Bic' = $J - \ln(N) \cdot (M - P)$, where 'J' is Hansen's J statistic, 'M' the number of moments and 'P' the number of model parameters. 'N' is the number of observations. We perform a BIC discrimination test according to Augustin/Sauerbrei/Schumacher (2005) and Buckland/Burnham/Augustin (1997). Using bootstrap methods we generate an empirical distribution of each model's BIC and test the null hypothesis H0: BIC of model (1) greater or equal BIC of model (2) and (3) respectively. We report the t-Statistic.

'***' denotes the significance at the 1% level, '**' refers to the significance at the 5% level and '*' to the 10% level significance. All variables are estimated and defined as described in 3. Data and Estimation Procedure.

(continued)

Table 4 (*Continued)*

Panel D: First-Stage Regressions Results

	growth risk model			spread risk model			income risk model			
First-Stage Regression for instrumented Variable:	Grrisk	Finrisk	Oprisk	Sprisk	Finrisk	Oprisk	Inrisk	Prodrisk	Finrisk	Oprisk
Adj. R^2	0.34	0.26	0.26	0.05	0.29	0.25	0.17	0.36	0.26	0.20
Partial R^2 of excluded Instruments	0.36	0.28	0.28	0.09	0.31	0.28	0.20	0.39	0.28	0.23
Shea Partial R^2	0.22	0.17	0.28	0.08	0.26	0.29	0.08	0.22	0.14	0.10
F-Test of excluded Instruments,	12.61	13.81	11.58	2.71	12.27	10.09	8.55	24.39	11.66	7.49
Stat (p-val)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Underident. Test, Stat. (p-val)	31.72 (0.00)			16.75 (0.02)			10.84 (0.05)			
Weak ident. Test; Stat.	4.82			2.22			1.65			
Overrident. Test, Stat. (p-val)										
2SLS / GMM2s	7.77 (0.17)			10.29 (0.11)			6.66 (0.15)			
Fuller(1)	6.75 (0.24)			7.44 (0.28)			4.70 (0.32)			
Fuller(4)	7.13 (0.21)			9.14 (0.17)			6.04 (0.20)			
Weak Instrument Robust Inference:										
Anderson-Rubin Wald test, F-Stat (p-val)	11.32 (0.00)			9.59 (0.00)			12.74 (0.00)			
Anderson-Rubin Wald test, χ^2-Stat. (p-val)	95.01 (0.00)			91.03 (0.00)			106.98 (0.00)			
Stock-Wright LM S statistic, Stat. (p-val)	43.48 (0.00)			40.43 (0.00)			42.2 (0.00)			

Notes:

Panel D of Table 4 presents first stage regression results and instrument diagnostics from estimating the three competing models in Table 4, Panel A to C. For each of our three models the instrumented variables are given in the second row of this panel. Each column below states the first stage regression results for the instrumented variable. We report Adjusted R^2 (Adj.-R^2), Partial R^2 of excluded instruments, Shea Partial R^2, as well as the F-Test of excluded instruments and its p-value in parentheses. We report the Kleibergen Paap rk LM statistic as a test for underidentification and the Kleibergen-Paap Wald F-statistic for Weak instrument identification. For each of our IV regressions (2SLS, GMM2s, Fuller(1), Fuller(4)) we report the Hansen J statistic and the corresponding p-value as a test for overidentification. The Underidentification Test is rejected in each of the models and the Overidentification Test (H_0: Instruments are valid and the excluded instruments are correctly excluded from the estimated equation) is not rejected, indicating a well specified equation.

Table 5

Encompassing

	Exp Sign.	OLS	2SLS	GMM2s	Fuller(1)	Fuller(4)
ln(growth risk)	+	0.29***	0.74**	0.72**	0.86*	0.56***
ln(spread risk)	+	0.04	-0.36	-0.39	-0.51	-0.13
ln(income risk)	+	0.14**	0.14	0.17	0.19	0.08
ln(productivity risk)	-/+	-0.16***	-0.65*	-0.63*	-0.81	-0.43***
ln(financial risk)	+	-0.33***	-1.73	-1.62	-2.14	-1.13**
ln(operating risk)	+	0.12*	-0.2	-0.21	-0.36	0.03
ln(income_to_Equity)	-	-0.08***	-0.04	-0.03	-0.02	-0.06**
Cons		-1.17***	-3.03*	-3.13**	-3.78	-1.95***
Adj. R^2 / Gen. Adj. R^2		0.45	0.40			
BIC / Gen. BIC		240.84	-6.98			
N		212	212	212	212	212
Underident. Test, Stat (p-val)			2.48 (0.65)			
Weak ident. Test, Stat (p-val)			0.30			
Overident. Test, Stat (p-val)			3.60 (0.31)	3.60 (0.31)	2.46 (0.48)	6.61 (0.09)

Notes:

This table presents OLS and Instrumental Variable regression estimates of the determinants of market beta. The dependent variable in each model is the natural logarithm of firm i's Market Beta (β_i). In each regression we include all Intrinsic Business risk proxies, i.e. growth-, spread- and income risk and last productivity risk.

Regarding the IV estimation we report two-stage-least-squares (2SLS) and Generalized Method of Moments (GMM2s) instrumental variable regression results as well as Fuller(1) and Fuller(4) estimates of the same model appropriate in the case of weak instruments. For 2SLS, Fuller(1) and Fuller(4) are the estimates efficient for homoscedasticity only and statistics are robust to heteroscedasticity. For the GMM2s estimation are the estimates efficient for arbitrary heteroscedasticity and statistics robust to heteroscedasticity.

For each variable the expected coefficient sign is reported. We report Adjusted R^2 ('Adj.-R^2'), the Bayesian Information Criterion ('BIC') for OLS estimation and Pesaran/Pesaran's (2009) 'Generalized-Adjusted-R^2' ('Gen.Adj.R^2') for the model estimated by the instrumental variable method. We further implement 'Generalized BIC' (see Andrews/Lu 2001, p.125). 'Gen. BIC' is calculated according to: 'Gen. Bic' = J – ln(N) · (M – P), where 'J' is Hansen's J statistic, 'M' the number of moments and 'P' the number of model parameters. 'N' is the number of observations.

For each IV regression we further report the main First Stage regression results, namely the Kleibergen Paap rk LM statistic as a test of underidentification and the Kleibergen-Paap Wald F statistic for Weak instrument identification. For each of our IV regressions we report the Hansen J statistic as a test for overidentification.

For the estimated IV regression we use the following instruments: IV growth risk(1), IV growth risk(2), IV spread risk(1), IV spread risk(2), IV income risk(1), IV operating risk(1), IV financial risk(1), IV financial risk(2), IV financial risk(4). Instruments as defined in Appendix 3.

'***' denotes the significance at the 1% level, '**' refers to the significance at the 5% level and '*' to the 10% level significance. All variables are estimated and defined as described in 3. Data and Estimation Procedure.

Table 6

Robustness

Panel A: NIOP Accounting Flow, various time intervals

		OLS			IV - Fuller4		
	Exp Sign.	growth risk model (1)	spread risk model (2)	income risk model (3)	growth risk model (1)	spread risk model (2)	income risk model (3)
1980-1989							
ln(growth risk)	+	0.29***			0.57***		
ln(spread risk)	+		0.17***			0.43	
ln(income risk)	+			0.17***			0.44
ln(productivity risk)	-/+			-0.18***			-0.52***
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	yes
Adj. R^2 / Gen. Adj. R^2		0.28	0.26	0.23	0.31	0.26	0.35
BIC / Gen. BIC		161.23	165.74	183.46	-18.95*	-9.95	-14.82
N		262	262	262	262	262	262
Vuong-Selection-Test growth risk model to:			0.49	1.03			
Underident. Test, Stat (p-val)					20.13 (0.00)	14.25 (0.05)	5.31 (0.38)
Weak ident. Test, Stat					2.87	2.30	0.72
Overident. Test, Stat (p-val)					8.66 (0.12)	10.59 (0.11)	5.43 (0.25)
1985-1994							
ln(growth risk)	+	0.34***			0.55***		
ln(spread risk)	+		0.07***			0.27	
ln(income risk)	+			0.20***			0.61***
ln(productivity risk)	-/+			-0.05			0.02
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	Yes
Adj. R^2 / Gen. Adj. R^2		0.46	0.20	0.30	0.37	0.29	0.33
BIC / Gen. BIC		111.42***	222.33	188.75	-26.60***	-18.62	-18.85
N		277	277	277	277	277	277
Vuong-Selection-Test growth risk model to:			5.77***	4.35***			
Underident. Test, Stat (p-val)					18.73 (0.00)	23.73 (0.00)	10.43 (0.06)
Weak ident. Test, Stat (p-val)					2.49	2.58	1.47
Overident. Test, Stat (p-val)					1.67 (0.89)	8.50 (0.20)	5.08 (0.28)
1995-2004							
ln(growth risk)	+	0.35***			1.01***		
ln(spread risk)	+		-0.04			0.50**	
ln(income risk)	+			0.08			0.97***
ln(productivity risk)	-/+			-0.02			-0.28
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	yes
Adj. R^2 / Gen. Adj. R^2		0.17	0.12	0.12	0.17	0.14	0.16
BIC / Gen. BIC		733.69***	751.64	756.25	-20.51*	-12.66	-14.36
N		307	307	307	307	307	307
Vuong-Selection-Test growth risk model to:			1.78*	2.95***			
Underident. Test, Stat (p-val)					26.78 (0.00)	29.66 (0.00)	17.18 (0.00)
Weak ident. Test, Stat (p-val)					4.02	3.74	2.78
Overident. Test, Stat (p-val)					8.73 (0.12)	9.67 (0.14)	10.62 (0.03)

(continued)

Table 6 *(continued)*

Panel B: Industry Dummies, NIOP Accounting Flow, 1990-1999, OLS				
	Exp Sign.	growth risk model (1)	spread risk model (2)	income risk model (3)
ln(growth risk)	+	0.15**		
ln(spread risk)	+		0.03	
ln(income risk)	+			0.12**
ln(productivity risk)	-/+			0.01
Industry Dummies		yes	yes	yes
ln(Fin,Op,IE,Cons)		yes	yes	yes
Adj. R^2		0.59	0.56	0.57
BIC		204.22***	221	218.88
N		212	212	212
Vuong-Selection-Test growth risk model to:			2.82***	1.67*

Panel C: Industry Dummies, NIOP Accounting Flow, 1990-1999, IV							
	Exp Sign.	growth risk model (1)	spread risk model (2)	income risk model (3)	growth risk model (1)	spread risk model (2)	income risk model (3)
			2SLS			GMM2s	
ln(growth risk)	+	0.27***			0.24**		
ln(spread risk)	+		0.23*			0.21*	
ln(income risk)	+			0.25			0.28
ln(productivity risk)	-/+			-0.03			0.02
Industry Dummies		yes	yes	yes	yes	yes	yes
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	yes
			Fuller(1)			Fuller(4)	
ln(growth risk)	+	0.35**			0.31**		
ln(spread risk)	+		0.50			0.30	
ln(income risk)	+			0.60			0.27
ln(productivity risk)	-/+			-0.03			-0.03
Industry Dummies		yes	yes	yes	yes	yes	yes
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	yes

Panel D: Main First Stage Regression Result and Model Selection Criteria for IV Regression			
	growth risk model (1)	spread risk model (2)	income risk model (3)
Under. Ident. Test, Stat (p-val)	15.91 (0.01)	9.94 (0.19)	6.2 (0.29)
Weak ident. Test, Stat (p-val)	3.03	1.13	0.99
Overident. Test, Stat (p-val)			
2SLS / GMM2s	8 (0.15)	7.49 (0.28)	8.40 (0.07)
Fuller(1)	7.38 (0.19)	5.06 (0.33)	7.00 (0.13)
Fuller(4)	7.69 (0.17)	6.96 (0.33)	8.40 (0.08)
Gen. Adj. R^2	0.57	0.56	0.56
Gen. BIC	-24.10***	-19.70	-19.92
N	212	212	212

Notes:
Panel A presents OLS and Fuller(4) instrumental regressions results for NIOP Accounting Flow regarding a variation of time spans. Instead of our main results' time interval 1990-1999 we estimate the same models for the times 1980 to 1989, 1985 to 1994 and 1995 to 2004.

Panel B, C and D present detailed estimation results if industry dummy variables are used for our main time period 1990-1999. We match each firm to one of eleven industries according to Fama/ French's 12 Industry Portfolio Sic Classification (financials are dropped).
In particular the dependent variable in each model is the natural logarithm of firm i's 'Market Beta' ('β_i'). We estimate three different models, namely the 'growth risk model', the 'spread risk model' and the 'income risk model':
For the instrumental variable regression we instrument 'growth risk' by the standard deviation of sales ('IV growth risk(1)') and the average growth of total assets ('IV growth risk(2)'). 'spread risk' is instrumented by standard deviation of the ratio debt in current liabilities to total assets ('IV spread risk(1)'), the standard deviation of interest expenses ('IV spread risk(2)') and the average growth of total assets ('IV spread risk(3)'). 'income risk' is instrumented by the standard deviation of the ratio net income to sales ('IV income risk(1)'). The variable 'productivity risk' is instrumented by the standard deviation of the ratio net income to average sales growth ('IV productivity risk(1)'). 'operating risk' is instrumented by the average of the ratio property, plant and equipment to total assets ('IV operating risk(1)') and the standard deviation of net income ('IV operating risk(2)'). Finally 'financial risk' is instrumented by the average of the ratio total long term debt to total assets ('IV financial risk(1)'), the average of the ratio interest expenses to operating income after depreciation ('IV financial risk(2)'), the average of the ratio total long term debt to common equity tangible ('IV financial risk(3)') and the average of the ratio total long term debt to total common equity ('IV financial risk(4)'). The variable 'income_to_Equity' is not instrumented since it is not measured with error.
For the OLS regressions we report Adjusted-R^2 ('Adj.-R^2') as well as the Bayesian Information Criterion ('BIC'). We also apply the Vuong Test to determine whether the Adj.-R^2 of one estimated model is significantly larger than another. We report the Vuong Z-statistic.
For IV regression diagnostics we report the Pesaran/Pesaran's (2009) 'Generalized-Adjusted-R^2' ('Gen.Adj.R^2') offering a model selection criterion for choosing between models estimated by the instrumental variable method. Further we implement 'Generalized BIC' (see Andrews/Lu 2001, p.125) providing a valid goodness of fit measure for the overall model. For each of the three models 'Gen. BIC' is calculated according to: 'Gen. BIC' = J – ln(N) · (M – P), where 'J' is Hansen's J statistic, 'M' the number of moments and 'P' the number of model parameters.
We perform a BIC (Gen. BIC in case of IV estimation) discrimination test according to Augustin/Sauerbrei/Schumacher (2005) and Buckland/Burnham/Augustin (1997). The null being H0: BIC (Gen. BIC) of model (1) greater or equal BIC (Gen. BIC) of model (2) and (3) respectively. Significance of this test is reported together with the BIC (Gen. BIC) value.
For each IV regression we further report the main First Stage regression results, namely the Kleibergen Paap rk LM statistic as a test of underidentification and the Kleibergen-Paap Wald F statistic for Weak instrument identification. For each of our IV regressions we report the Hansen J statistic as a test for overidentification. The Underidentification Test is rejected in each of the models and the Overidentification Test (H_0: Instruments are valid and the excluded instruments are correctly excluded from the estimated equation) is not rejected, indicating a well specified equation.
'N' is the number of observations. The number of observations varies among Panel A due to different data basis in different time intervals.
'***' denotes the significance at the 1% level, '**' refers to the significance at the 5% level and '*' to the 10% level significance. All variables are estimated and defined as described in 3. Data and Estimation Procedure.

Table 7

Robustness - Different measurement of spread risk

Panel A: NIOP Accounting Flow, 1990-1999, OLS				
	Exp Sign.	growth risk model (1)	Mod.spread risk model (2)	income risk model (3)
ln(growth risk)	+	0.41***		
ln(spread risk)	+		0.14***	
ln(income risk)	+			0.39***
ln(productivity risk)	-/+			-0.15***
ln(Fin,Op,IE,Cons)		yes	yes	yes
Adj. R^2		0.33	0.18	0.29
BIC		317.36***	373.12	338.43
N		288	288	288
Vuong-Selection-Test growth risk model to:			3.14***	1.22

Panel B: NIOP Accounting Flow, 1990-1999, IV							
	Exp Sign.	growth risk model (1)	Mod.spread risk model (2)	income risk model (3)	growth risk model (1)	Mod.spread risk model (2)	income risk model (3)
			2SLS			GMM2s	
ln(growth risk)	+	0.52***			0.53***		
ln(spread risk)	+		0.33***			0.28***	
ln(income risk)	+			0.65***			0.76***
ln(productivity risk)	-/+			-0.08			-0.06
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	yes
			Fuller(1)			Fuller(4)	
ln(growth risk)	+	0.55***			0.55***		
ln(spread risk)	+		0.48**			0.41***	
ln(income risk)	+			0.78**			0.68***
ln(productivity risk)	-/+			-0.02			-0.07
ln(Fin,Op,IE,Cons)		yes	yes	yes	yes	yes	yes

Panel C: Main First Stage Regression Result and Model Selection Criteria for IV Regression			
	growth risk model (1)	Mod.spread risk model (2)	income risk model (3)
Under. Ident. Test, Stat (p-val)	36.63 (0.00)	16.54 (0.02)	9.14 (0.10)
Weak ident. Test, Stat (p-val)	6.11	2.17	1.30
Overident. Test, Stat (p-val)			
2SLS / GMM2s	8.17 (0.15)	11.48 (0.07)	4.27 (0.37)
Fuller(1)	7.73 (0.17)	8.24 (0.22)	3.44 (0.49)
Fuller(4)	7.83 (0.17)	9.72 (0.14)	4.13 (0.39)
Gen. Adj. R^2	0.19	0.16	0.22
Gen. BIC	-21.43	-12.84	-17.41
N	288	288	288

(continued)

Table 7 *(continued)*

Robustness - Different Accounting Flows

Panel D: FFOP Accounting Flow, 1990-1999

		OLS			IV - Fuller4		
	Exp Sign.	growth risk model (1)	spread risk model (2)	income risk model (3)	growth risk model (1)	spread risk model (2)	income risk model (3)
ln(growth risk)	+	0.28***			0.62***		
ln(spread risk)	+		0.09***			0.70**	
ln(income risk)	+			0.23***			0.69***
ln(productivity risk)	-/+			-0.08			-0.32***
ln(financial risk)	+	0.06	-0.37*	-0.47**	1.77***	0.92	0.17
ln(operating risk)	+	0.21***	0.13***	-0.05	0.58***	0.62**	-0.14
ln(income_to_Equity)	-	-0.07***	-0.07***	-0.06***	-0.06***	-0.04	-0.03
Cons		-0.86***	-0.23	-0.82***	-1.25***	2.20*	-1.31***
Adj. R^2/ Gen. Adj. R^2		0.26	0.13	0.17	0.24	0.15	0.24
BIC / Gen. BIC		407.87***	457.81	449.43	-23.39***	2.63	-14.43
N		312	312	312	312	312	312
Vuong-Selection-Test growth risk model to:	Stat		3.56***	2.01**			
Underident. Test, Stat (p-val)					30.75 (0.00)	21.55 (0.00)	20.41 (0.00)
Weak ident. Test, Stat (p-val)					5.77	3.12	2.79
Overident. Test, Stat (p-val)					6.70 (0.24)	11.31 (0.08)	8.20 (0.08)

Panel E: WCOP Accounting Flow, 1990-1999

		OLS			IV - Fuller4		
	Exp Sign.	growth risk model (1)	spread risk model (2)	income risk model (3)	growth risk model (1)	spread risk model (2)	income risk model (3)
ln(growth risk)	+	0.24***			0.60***		
ln(spread risk)	+		0.10***			0.60***	
ln(income risk)	+			0.20***			0.65***
ln(productivity risk)	-/+			-0.04			-0.15
ln(financial risk)	+	0.35	-0.07	-0.09	1.98***	0.53	0.98
ln(operating risk)	+	0.21***	0.16***	0.00	0.71***	0.39**	-0.02
ln(income_to_Equity)	-	-0.08***	-0.08***	-0.07***	-0.07***	-0.09***	-0.04*
Cons		-0.92***	-0.29*	-0.84***	-1.35***	1.49**	-1.32***
Adj. R^2/ Gen. Adj. R^2		0.21	0.13	0.15	0.19	0.15	0.20
BIC / Gen. BIC		345.17***	370.76	369.89	-20.42***	-13.06	-17.49
N		259	259	259	259	259	259
Vuong-Selection-Test growth risk model to:	Stat		2.14**	1.71*			
Underident. Test, Stat (p-val)					22.38 (0.00)	20.15 (0.00)	12.00 (0.03)
Weak ident. Test, Stat (p-val)					3.69	2.7	1.63
Overident. Test, Stat (p-val)					8.51 (0.13)	8.92 (0.18)	5.55 (0.24)

Notes:

Panel A presents OLS regression results for a modified spread risk model (‘*Mod.spread risk model*’) during the time 1990 to 1999 based on the NIOP Accounting Flow. For the spread risk estimation we employ Chen/Roll/Ross’ (1986) inflation factor. For the same model specification Panel B presents IV estimates while Panel C presents First Stage regression results.
Panel D and E present OLS and Fuller(4) instrumental variable regression results where the firm i’s income is proxied by the ‘Funds Flow from Operations’ Accounting Flow (FFOP) and the ‘Working Capital from Operations’ (WCOP). We compute

FFOP according to: FFOP = (IBADJ+DP)/(CSHPRI·AJEX) on firm basis and WCOP according to: WCOP=(IBADJ+DP+TXDI)/(CSHPRI·AJEX) on firm basis. Panel D and E use the original notion of spread risk.

In particular the dependent variable in each model is the natural logarithm of firm i's Market Beta (β_i). We report detailed regression estimates for our main variables of interest growth-, spread- and income risk. For each variable the expected coefficient sign is reported. We further report Adjusted-R^2 ('Adj.-R^2') and the Bayesian Information Criterion ('BIC'). We also apply the Vuong Test to determine whether the Adj.-R^2 of one estimated model is significantly larger than another. We report the Vuong Z-statistic.

For 2SLS, Fuller(1) and Fuller(4) are the estimates efficient for homoscedasticity only and statistics are robust to heteroscedasticity. For the GMM2s estimation are the estimates efficient for arbitrary heteroscedasticity and statistics robust to heteroscedasticity.

We report the Kleibergen Paap rk LM statistic as a test of underidentification and the Kleibergen-Paap Wald F statistic for Weak instrument identification. For each of our IV regressions we report the Hansen J statistic as a test for overidentification. Further the Pesaran/Pesaran's (2009) 'Generalized-Adjusted-R^2' ('Gen.Adj.R^2') and 'Generalized BIC' (see Andrews/Lu 2001, p.125) is presented. We perform a BIC (Gen. BIC in case of IV estimation) discrimination test according to Augustin/Sauerbrei/Schumacher (2005) and Buckland/Burnham/Augustin (1997). The null being H0: BIC (Gen. BIC) of model (1) greater or equal BIC (Gen. BIC) of model (2) and (3) respectively. Significance of this test is reported together with the BIC (Gen.BIC) value.

We use the following instruments for IV regression: 'growth risk' is instrumented by the standard deviation of sales ('IV growth risk(1)') and the average growth of total assets ('IV growth risk(2)'). 'spread risk' is instrumented by standard deviation of the ratio debt in current liabilities to total assets ('IV spread risk(1)'), the standard deviation of interest expenses ('IV spread risk(2)') and the average growth of total assets ('IV spread risk(3)'). 'income risk' is instrumented by the standard deviation of the ratio net income to sales ('IV income risk(1)'). The variable 'productivity risk' is instrumented by the standard deviation of the ratio net income to average sales growth ('IV productivity risk(1)'). 'operating risk' is instrumented by the average of the ratio property, plant and equipment to total assets ('IV operating risk(1)') and the standard deviation of net income ('IV operating risk(2)'). Finally 'financial risk' is instrumented by the average of the ratio total long term debt to total assets ('IV financial risk(1)'), the average of the ratio interest expenses to operating income after depreciation ('IV financial risk(2)'), the average of the ratio total long term debt to common equity tangible ('IV financial risk(3)') and the average of the ratio total long term debt to total common equity ('IV financial risk(4)'). The variable 'income_to_Equity' is not instrumented since measured error is negligible.

'N' is the number of observations. The number of observations varies among the different Panels of this Table due to different data requirements for each Accounting Flow concept employed (Panel D and E). We performed the same estimations requiring for all data requirements of all Accounting Flows at the same time. The unreported results are qualitative similar but based on a slightly smaller number of observations.

'***' denotes the significance at the 1% level, '**' refers to the significance at the 5% level and '*' to the 10% level significance.