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MACROECONOMIC EFFECTS ON SYSTEMATIC RISK IN EUROPE. THE CASE OF CYCLICAL V. NON-CYCLICAL COMPANIES

This study explores macroeconomic and industry-level effects on corporate systematic risk (or beta) for European cyclical and noncyclical companies. We document the extent to which stock market betas fluctuate over time for both industry groups. In addition, we analyze the fundamental determinants of systematic risk. We find evidence that, although noncyclical industries market betas have a lower magnitude, after controlling for firms fundamental strength, macroeconomic conditions and different institutional environments, both types of industries are affected in the same manner by the variables incorporated in our study.

Keywords: *Systematic risk; Cyclical and non-cyclical industries; CAPM; Time-varying systematic risk; Real determinants; Industry risk.*

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МАКРОЕКОНОМІЧНІ ЕФЕКТИ НА СИСТЕМАТИЧНИЙ РИЗИК В ЄВРОПІ. ВИПАДОК ЦИКЛІЧНИХ ПРОТИ НЕЦИКЛІЧНИХ КОМПАНІЙ

У цьому дослідженні досліджується макроекономічний і галузевий вплив на корпоративний систематичний ризик (або бета-версію) для європейських циклічних і нециклічних компаній. Ми документуємо, якою мірою бета-версії фондового ринку коливаються з часом для обох галузевих груп. Крім того, ми аналізуємо основні детермінанти систематичного ризику. Ми знаходимо докази того, що, хоча ринкові бета-версії нециклічних галузей мають нижчу величину, після контролю за фундаментальною силою фірм, макроекономічними умовами та різними інституційними середовищами обидва типи галузей зазнають однакового впливу змінних, включених у наше дослідження.

Ключові слова: *систематичний ризик; циклічні та нециклічні галузі; CAPM; систематичний ризик, що змінюється в часі; реальні детермінанти; галузевий ризик.*

1. Introduction. In the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), and its descendants, such as the intertemporal CAPM (ICAPM; Merton, 1973) and the multifactor (beta pricing) models, the stock market beta is a significant determinant of expected stock returns (Ross, 1976; Fama and French, 1993, 1995, 2015). Given the extensive usage of betas by investors and corporate managers, and the fact that systematic risk and its determinants can vary significantly across industries (Fama and French, 1997), it is of great importance to examine empirically how betas are determined.

To the best of our knowledge, existing studies on the area are industry specific (among others see Muiruri, 2014; Drobetz et. al, 2016; Zhou, 2018). Thus, we contribute to the empirical literature by investigating systematic risk levels in cyclical and

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noncyclical industry groups and provide a general overview of beta behavior between the two adverse groups. Both the level and the drivers of systematic risk are essential for the estimation of the cost of equity capital, which is a key parameter to evaluate and identify profitable investment decisions. Therefore, both components are of esteemed importance for corporate financial managers. In this study, we address both issues.

First, we investigate the time-series and cross-sectional dynamics of systematic risk levels in the cyclical and noncyclical industries, based on a comprehensive sample of European listed companies. Second, we provide a detailed analysis of fundamental market risk determinants common for the two industry groups. Our results show that although the two industry groups exhibit different systematic risk levels, they are basically indifferent when it comes down to the underlying market risk factors.

Investigating the time-dimension of beta, Bos and Newbold (1984) argue that systematic risk levels are influenced by both changes in microeconomic factors (the market risk unique to the activities of a company) and macroeconomic conditions (the changes in global economic conditions or factors relevant to industry). This view is closely related to the theoretical work of Gomes et al. (2003) and the empirical asset pricing literature on time-varying betas (Bollerslev et al., 1988; Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001b; Lewellen and Nagel, 2006). Market beta appears to be higher under poor economic systems, yet lower during good economic states.

It is expected that such business cycle effects on systematic risk would be greater if an organization operates in industries that are more vulnerable to changes in global business conditions, thereby providing an explanation for industry-specific variations in the dynamics of systematic risk. Given the empirical evidence against constant betas, Mergner and Bulla (2008) explicitly model the time-varying behavior of betas for European industry portfolios and their results suggest that the state-space model with a random walk beta was the best model to fit their data.

Following this notion, we employ a conditional CAPM framework and receive time-varying estimates of monthly betas and analyze changes in the levels of both industry groups' risk over time. Estimated stock market betas fluctuate considerably during the sample period for both industry groups. Kalman filter-based estimates show that the average beta varies between 0.20 and 0.75 for cyclical industries, while for noncyclical industries it spans from 0.10 to 0.60, during the years of our sample period. As expected, the estimated betas for both types of industries peaked during the recent eurozone crisis from 2007 onwards, which has led to severe turbulences in the whole market. However, an interesting finding is that we also observe increased betas during the first years of the euro introduction suggesting that currency changes contribute to increasing market risk.

These findings strongly indicate that when assessing corporate risk levels, adjustment for time-variation in beta is key. In particular, depending on the constant beta of the OLS-based approach, equity cost estimates can lead to sub-optimal decisions in the process of capital budgeting.

Finally, we also focus on the determinants of both industries' betas. Building upon the existing literature, we argue that firm-level fundamentals, as well as macroeconomic and institutional factors will affect stock market betas. Using the panel regression methodology that includes a set of firm-specific, macroeconomic and institutional-related variables to explain the observed levels of systematic risk, we analyze the cross-sectional variation in stock market betas.

Our results suggest that although noncyclical industries' market betas remain of lower magnitude after controlling for firms' fundamental strength, macroeconomic conditions and different institutional environments, both types of industries are affected in the same manner by the variables incorporated in our study. Thus, we provide evidence that European cyclical and noncyclical groups of industries are more homogenous than expected, considering that noncyclical sectors are perceived to be less exposed to economic fluctuations. One possible explanation is that as global capital markets and economies become more integrated, we expect industries to be considered in a global context.

The remainder is structured as follows: Section 2 provides our research design and formulated hypotheses. Section 3 describes the sample selection and reviews the data. Section 4 presents and discusses our empirical findings. Finally, Section 5 concludes and discusses implications for financial decision makers.

2. Research Design and Hypothesis Development. The main scope of the present study is to examine the differences in systematic risk levels between cyclical and noncyclical industries. Thus, this is the first systematic attempt to derive general inferences on cyclical and noncyclical industries' stock market betas. Our empirical research design employs both portfolio-based and regression-based analysis.

Furthermore, numerous studies (Bollerslev et al., 1988; Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001b; Lewellen and Nagel, 2006) report evidence against beta consistency, providing that estimating time-varying betas and including them in the CAPM model provides better presentation of the market, as all economic prices vary over time. Adopting this intuition, we also employ a time-varying beta approach using the Kalman filter procedure. Finally, we incorporate firm-level, macroeconomic and institutional factors in our analysis, since the available data indicate that they determine industries' systematic risk levels.

2.1. Firm-Level Factors. Prior research provides evidence that financial accounting variables are important in determining beta (Beaver et al., 1970; Logue and Merville, 1972; Breen and Lerner, 1973; Rosenberg and McKibben, 1973; Melicher, 1974; Ben-Zion and Shalit, 1975; Gahlon and Gentry, 1982; Campbell and Mei, 1993 and Campbell and Vuolteenaho, 2004). Accounting variables used in prior studies can be divided into five categories: (1) operating leverage, (2) financial leverage, (3) corporate liquidity, (4) growth opportunities and (5) default risk. Our choice variable, namely the FSCORE, incorporates to a certain extent the following categories: (1) profitability, (2) leverage, liquidity, and source of funds and (3) operating efficiency. Thus, we argue that it reflects a large proportion of the degree of uncertainty inherent in a firm's business model.

Furthermore, the FSCORE has become particularly popular among US investors as a stock screening tool (Novy-Marx, 2014) but has also been used in US academic literature for various purposes. As an example, it has been applied to predict future firm profitability (Fama and French, 2006), institutional investor demand (Choi and Sias, 2012), and as an instrumental variable to test how public fundamental information is incorporated into prices (Turtle and Wang, 2017).

We adopt the intuition by Hyde (2018) and Ng and Shen (2019) and extend the scope of Piotroski's (2000) FSCORE measure. Since low values of FSCORE indicate deterioration in firms' fundamentals, one should expect a negative relation between FSCORE and beta.

Recent studies (Saravia et al., 2020 and Chincarini et al., 2020) go beyond accounting figures and examine how systematic risk varies over the lifecycle of the firm. Their main argumentation lies in the notion that firm characteristics and structure of companies change over time. Thus, the inclusion of firm lifecycle variable could mitigate the potential impact of omitted variables on econometric results, as these variables can proxy for factors that vary over the lifecycle of the firm but are difficult to measure quantitatively. Both studies conclude that the coefficient of systematic risk tends to fall in magnitude as firm age increases.

We incorporate Hribar and Yehuda's (2015) lifecycle measure, based on sales growth, capital expenditures, net equity transactions and firm age. In line with the above-mentioned studies, we expect a negative relation between LIFECYCLE and beta.

2.2. Macroeconomic Factors. Cyclical industries are closely related to the fluctuation of the economy, whereas noncyclical industries are less affected by the rise or fall of the market. Thus, we incorporate various macroeconomic variables to account for the level of uncertainty under different states of the business cycle. Existing studies on the effect of economic conditions on the variation of beta coefficients incorporate mainly industrial production and inflation as relevant variables.

Given the fact that we (a) use an integrated European market sample and (b) we classify stocks into a cyclical industry group and a noncyclical industry group, rather than focusing on a per-industry analysis, we employ five country level variables proxying for macroeconomic conditions to control for a broader economy-related effects in beta risk: (1) country's economic stability, (2) country's economic development, reflected in the quality of the country's business networks and support industries, (3) country's analyst activity, and two proxies for trading frictions namely, (4) country's average trading volume and (5) country's index for transaction costs.

Times of high (low) economic instability and economic decay can be characterized by high (low) levels of investor uncertainty about future earnings of cyclical companies, and thus we expect beta to be higher (lower) during such periods. On the other hand, we expect stable or slightly higher (lower) noncyclical industries' beta during periods of economic instability and market inefficiency.

High trading frictions may be translated into deferred investment or reduced invested capital. In both cases, there is an increasing uncertainty about the continuation value of a cyclical firm, since cyclical firms are more prone to external financing to support or extent their business. Therefore, high trading frictions should be an important factor leading the observed systematic risk levels of cyclical industries. However, businesses in non-cyclical industries have sticky demand, in the sense that the demand for their product or service is always there. As a result, their need for external financing is expected to be lower as their sales generate the needed resources. Thus, we expect that trading frictions will have less impact, if any, on noncyclical industries' market betas.

Finally, we consider the analyst activity index proposed by Isidro and Raonic (2012), as a more direct proxy of information uncertainty. Analysts put pressure on corporate insiders to report reliable and high-quality financial information by thoroughly scrutinizing information on financial statements and other sources (e.g., Lang, Lins, and Miller, 2003; Fang, 2008). From an investor perspective, accurate and high-quality information strengthens their estimations about future corporate income streams. Since higher values of the analyst index are presumed to have a negative impact on informational uncertainty, we expect that the analyst index is negatively related to systematic risk levels.

2.3. Institutional Factors. Empirical industry-specific studies on the determinants of systematic risk provide evidence that different institutional environments may also cause variations in betas. Following this intuition, we also consider country-level proxies associated with investors' protection, political risk and reporting standards.

La Porta et al. (1998) argue that common law countries provide higher investor protection than civil law countries. Investors are willing to pay more for financial assets, when their rights are better protected by law, since they acknowledge that more of the firm's profits will come back to them as interest or dividends. Legal risk can be systematic (and thus beta-increasing) given that weak legal protection of investors' financial claims is a non-fully hedged investment risk. To proxy for investor protection, we use the index measure provided by La Porta et al. (2006).

Political risk entails the effect of tax policies (McGrattan and Prescott, 2005; Sialm, 2009) and uncertainty regarding regulations and government policy (Pastor and Veronesi, 2012; Baker, Bloom, and Davis, 2016). It also requires, by definition, government-initiated seizure of private properties or production and sliding forms of expropriation, such as unforeseen taxes or benefit royalties (Knudsen, 1974; Minor, 1994). It also covers the volatility of related government policies (Brewer (1983, 1993)), as well as the strength of the legal system, especially with regard to property rights enforcement. Political risk can be systematic given that; high volatility of related government policies leads to increased uncertainty about companies' future income streams and/or investors' financial claims on international investment. To proxy for political risk, we use the index measure provided by the International Country Risk Guide (ICRG).

Lambert et al. (2007) investigate whether and how the different standard of accounting knowledge about a business is reflected in the cost of capital in different legal environments. They show that there is a direct impact because higher quality disclosures reduce the covariances between a company and the cash flows of other businesses, which is non-diversifiable and therefore systemic. Xin and Yang (2019) report evidence that accounting information quality is significantly and negatively related to systematic risk, and thus improving accounting information quality reduces systematic risk levels. Following Xin and Yang (2019), we also employ managerial discretion over earnings as an indicator of accounting information quality. To proxy for managerial discretion over earnings, we employ the earnings management score provided by Leuz et al. (2003).

Overall, we expect macroeconomic and institutional factors to affect systematic risk levels for cyclical industries. Since noncyclical industries provide goods and services that are always needed, we do not expect macroeconomic and institutional factors to play an important role in determining their market betas. That being said, our formulated hypothesis regarding the impact of firm-specific, macroeconomic and institutional factors on market betas, is as follows:

H1: Since high FSCORE values indicate strong key principles, we expect a negative relation between FSCORE and betas for cyclical industries. For noncyclical industries, we expect the beta coefficients' variations to be of lower magnitude conditional on the FSCORE variable.

2: For cyclical industries we expect that the coefficient of systematic risk tends to fall in magnitude as firm age increases. In case of noncyclical industries, we expect the beta coefficients' variations to be of lower magnitude conditional on the LIFECYCLE variable.

H3: For cyclical industries we expect a negative relation between MACROEC/BUSOPH variables and betas since economic stability and economic development suggest lower market betas. For noncyclical industries, we expect beta coefficients' variations to be of lower magnitude.

H4: For cyclical industries we expect a positive relation between TCOST variable and betas, and a negative relation between DVOL variable and betas, since high trading frictions suggest higher market betas. For noncyclical industries, we expect beta coefficients' variations to be of lower magnitude.

H5: For cyclical industries, we expect a negative relation between ANALYST variable and betas since high analyst activity increases information certainty and leads to lower betas. In case of noncyclical industries, we expect beta coefficients' variations to be of lower magnitude conditional on the ANALYST variable.

H6: For cyclical industries, we expect a negative relation between INVPROT variable and betas since strong investor protection leads to lower levels of systematic risk. In case of noncyclical industries, we expect beta coefficients' variations to be of lower magnitude conditional on the INVPROT variable.

H7: For cyclical industries, we expect a negative relation between PR variable and betas since low levels of political risk lead to lower levels of systematic risk. In case of noncyclical industries, we expect beta coefficients' variations to be of lower magnitude conditional on the PR variable.

H8: For cyclical industries, we expect a positive relation between EM variable and betas since high managerial discretion over earnings suggests poor accounting quality, which leads to increased levels of systematic risk. In case of noncyclical industries, we expect beta coefficients' variations to be of lower magnitude conditional on the EM variable.

3. Data, Sample Formation, and Variable Measurement

3.1. Data and Sample Formation. Our sample consists of non-financially listed firms from 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Following Titman et al. (2013), we require each country to have at least 30 stocks in any year of participation in the sample to ensure a reasonable number of firms for our portfolio tests and cross-sectional regression tests. Furthermore, the above-mentioned countries are the constituents of aggregated common risk factors.

We collect industry codes, industry names, accounting data and monthly returns from Worldscope and Datastream International files. We include common stocks listed on the major stock exchange in each country, from both active and defunct data files from Datastream and Worldscope to avoid survivorship bias. Closed-end funds, trusts, REITs, ADRs, units of beneficial interest, and other financial firms are excluded from the sample. Financial firms are excluded. We further exclude, firms with industry names of "Na", "Unquoted equities" and "Unclassified" from our sample, since we require a classification into cyclical and noncyclical industries.

Accounting data is obtained for the period 1988–2016, while monthly returns are obtained for the period of 1988-2018 (forward looking returns). Returns and other firm-level variables are calculated in U.S. dollars. Since we use an integrated European sample, we employ the risk factors from AQR and from Kenneth R. French website (The risk factors for our European stocks sample are taken from Kenneth R. French website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library and AQR: https://www.aqr.com/Insights/Datasets)[1].

To detect suspicious returns, we exclude from our stock sample with price returns above 300% or less than 50% [2] (that is reversed within one month (Ince and Porter, 2006). Following the proposed methodology, if Rt or Rt-1 is greater than 300% and (1 + Rt)(1 + Rt-1) - 1 is less than 50%, both returns are discarded). Return data are winsorized at the upper and lower one percentile to mitigate the impact of outliers and to eradicate data errors.

After all data cleaning steps, we remain with 6,219 non-financial listed firms of which 4,937 firms belong to cyclical industries, whereas 1,282 firms belong to noncyclical industries. We provide an Appendix with details on the classification of industries into cyclical and noncyclical, as well as the percentage of participation of each industry in the total sample. To be consistent with the risk factors' returns from Kenneth R. French website, our sample period spans from July 1990 to June 2018.

All firm-level variables are winsorized at the 1% and 99% level to mitigate the impact of outliers. The firm-year panel used in cross-sectional regressions is achieved by combing annual accounting data and monthly stock market returns (including beta estimates) on a fiscal year-end basis. This procedure allows us to investigate whether fiscal year-end accounting variables explain fiscal year-end systematic risk levels. The final annual sample used in Piotroski's (2000) Fscore and Hribar and Yehuda's (2015) Lifecycle portfolio analysis spans the period from 1990 through 2016, with forward looking returns from July 1991 to June 2018. Table 1 presents the distribution of firms and firm-year observations with respect to the firms' country code and over time respectively, both for cyclical and noncyclical industries.

The table presents the distribution of firms and firm-year observations with respect to the firms' country code over, both for cyclical and noncyclical industries. The total sample consists of 6,219 non-financial listed firms from 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. 4,937 firms are from cyclical industries, whereas 1,282 firms are from noncyclical industries. Accounting data and monthly returns come from Worldscope and Datastream International files.

1 The risk factors for our European stocks sample are taken from Kenneth R. French website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library and AQR: https://www.aqr.com/Insights/Datasets

2 Following the proposed methodology, if Rt or Rt-1 is greater than 300% and (1 + Rt)(1 + Rt-1) - 1 is less than 50%, both returns are discarded.

Table 1. **Sample Overview**

Cyclical		NonCyclical	
Country	**Number of companies**	**Country**	**Number of companies**
Austria	103	Austria	27
Belgium	126	Belgium	67
Denmark	162	Denmark	56
Finland	189	Finland	36
France	736	France	180
Germany	1,052	Germany	269
Greece	372	Greece	104
Ireland	31	Ireland	11
Italy	160	Italy	54
Netherlands	80	Netherlands	20
Norway	127	Norway	22
Portugal	40	Portugal	10
Spain	79	Spain	35
Sweden	253	Sweden	83
Switzerland	123	Switzerland	55
The U.K.	1,304	The U.K.	253
Total	**4,937**	**Total**	**1,282**

Cyclical		NonCyclical	
Calendar Year	**Obs.**	**Calendar Year**	**Obs.**
1991	200	1991	62
1992	215	1992	64
1993	229	1993	70
1994	261	1994	77
1995	295	1995	86
1996	324	1996	97
1997	367	1997	109
1998	416	1998	122
1999	509	1999	144
2000	648	2000	171
2001	875	2001	209
2002	981	2002	223
2003	1,147	2003	269
2004	1,231	2004	288
2005	1,309	2005	307
2006	1,471	2006	354
2007	1,623	2007	410
2008	1,720	2008	439
2009	1,778	2009	462
2010	1,805	2010	477
2011	1,813	2011	477
2012	1,831	2012	493
2013	1,828	2013	490
2014	1,792	2014	478
2015	1,944	2015	519
2016	4,018	2016	1,039
Total	**30,630**	**Total**	**7,936**

3.2. Measurement of Firm-Level Variables

Existing literature provides evidence that financial accounting variables affect firms' systematic risk. We aim for a more general overview of how investors assess and interpret the information contained in reported accounting figures. Thus, we incorporate Piotroski's (2000) FSCORE, which measures the fundamental strength of sample companies. It is based on the sum of nine binary indicator variables that capture different aspects of the firm's financial strength (or weakness). If the underlying condition is true, the indicator variable takes the value of one, otherwise it takes zero. The nine conditions are:

1) positive net income before extraordinary items is positive;
2) positive cash flow from operations;
3) positive change on an annual basis for return on assets;
4) cash flow from operations exceeds net income before extraordinary items;
5) negative change in leverage on an annual basis;
6) positive change in liquidity on an annual basis;

7) the firm did not issue shares;

8) positive change in gross margin on an annual basis;

9) positive change in turnover on an annual basis.

An FSCORE between 7 and 9 indicates strong fundamentals, while an FSCORE between 0 and 3 indicates weak fundamentals.

Saravia et al (2020) and Chincarini et al. (2020) examine how systematic risk varies over the lifecycle of the firm. Building upon this insight, we follow Hribar and Yehuda (2015), and classify firms into three life cycle stages (i.e. growth, maturity and decline), based on sales growth (noted by SG, hereafter), capital expenditures (noted by CAPEX, hereafter), net equity transactions (noted by NET, hereafter) and firm age (AGE, hereafter). SG is measured by the cumulative sales growth rate of the last two years. CAPEX is measured as the sum of capital expenditures and R&D expenses, scaled by total assets. NET is measured as the difference between the annual change in total shareholders' equity and the annual net income, scaled by total assets. AGE is the number of years from the first year that a firm has available data on Datastream International and Worldscope.

We standardize each of the above four variables by subtracting their mean and dividing it by its standard deviation and then adding them together to construct a single measure of the firms' life cycle stage (noted by LCS, hereafter). We then rank firms into five quintiles, based on LCS and consider only the top, bottom, and middle quintiles in our tests. Accordingly, top, bottom, and middle quintile consist of firms at the growth stage, maturity stage and decline stage, respectively.

Raw stock returns are calculated starting six months after the financial year-end to ensure the latest year-end book values are available using the return index provided by Datastream (item RI), which is defined as the theoretical growth in the value of a share-holding unit of equity at the closing price applicable on the ex-dividend date. The raw equity return for a firm for month j is calculated as: $rj = RI_{(j+1)}\ RI_{j-1}$.

3.3. Measurement of Macroeconomic and Institutional factors

In addition to firm-level factors (FSCORE and LIFECYCLE variables), our model also incorporates macroeconomic variables, which represent the level of uncertainty induced by the overall economy. However, systematic risk's levels may also vary across different institutional settings. Thus, we also employ variables that proxy for institutional factors. Data for country-level variables are available from various public sources. We divide country-level variables into two categories: a) country-level variables associated with macroeconomic factors and b) country-level variables associated with institutional factors.

The first set of country-level factors is associated with macroeconomic factors. In this study, we consider a more comprehensive set of factors intended to capture the complexity of the country's degree of development. Specifically, we employ Isidro and Raonic's (2012) macro economy proxy (MACROEC), which captures the country's economic stability. Data for MACROEC are taken from Isidro and Raonic (2012).

We also use the business sophistication (BUSOPH) score from the Global Competitiveness Index (World Economic Forum, 2007), which reflects the quality of the country's business networks and supporting industries. The score ranges from one to seven, with higher values given to countries with a relatively high degree of economic development.

We also employ two country-level factors associated with trading frictions. First, we use the average trading volume (DVOL, hereafter) in dollars, across all of the stocks in a given country. A higher value for DVOL is associated with lower trading frictions. Data for DVOL are taken from Watanabe et al. (2013).

Then, we use the index of trading costs (TCOST) used by Chan, Covrig, and Ng (2005) and Chui, Titman, and Wei (2010) to proxy for transaction costs. A country with an index higher indicates higher trading frictions. Data for TCOST are taken from Chan et al. (2005) & Chui et al. (2010).

Finally, we consider analyst activity (ANALYST, hereafter) as a proxy for information uncertainty. ANALYST is the first principal component of analyst forecast accuracy and the number of analysts following the firm. A higher value for the ANALYST index is presumed to have a negative impact on information uncertainty. Data for ANALYST are taken from Isidro and Raonic (2012).

The second set of country-level factors is associated with institutional factors. Starting with La Porta et al. (2005), we employ Investor Protection index (INV PROT) to proxy the legal protection guaranteed to investors. Data for INV PROT are taken from La Porta et al. 2005.

We take the political risk index (PR, hereafter) from the International Country Risk Guide (ICRG), which is the average of monthly estimates of political uncertainty measures, such as government stability and bureaucracy quality. A relatively high value of PR indicates a lower level of political risk.

We employ the earnings management score (EM, hereafter) estimated by Leuz et al. (2003), as a proxy of managerial discretion over earnings. The score is the percentage ranking of two metrics of earnings smoothing (reduced variability of reported earnings by altering operating accruals and correlation between operating accruals and operating cash flows) and two metrics of earnings discretion (magnitude of operating accruals relative to that of operating cash flows and small loss avoidance). A higher value of EM indicates greater managerial discretion over earnings.

3.4. Time-varying Systematic Risk Component

Following existing literature, we adopt the idea that estimates of the OLS market model only represent an average beta, which would be indistinguishable from that of the overall market, whereas the true beta of the stock outlines entirely different risk characteristics. Thus, we also provide evidence of a time-varying systematic risk component.

As our primary interest is in the overall stock market beta rather than in other beta variables that account for various dimensions of systematic risk, we conduct our research on the theoretical basis of CAPM. In addition, as the most parsimonious model, the CAPM is preferable from an econometric viewpoint, reducing the number of parameters to be calculated in the dynamic framework[3]. To obtain time-varying monthly beta estimates, we use the Kalman filtering approach.

3 Our analysis presented in the next section, reveals that stock market betas based on CAPM- and Fama and French (1993 & 2015)- are very similar for both cyclical and noncyclical companies. Therefore, we hypothesize that omitting other risk factors does not bias against our time varying stock market beta estimates.

This requires formulating the standard CAPM in a state-space framework, where the asset's exposure to the overall market is an unobserved state variable following some underlying stochastic process. We also assume that the stock market beta evolves according to a random walk. Based on this assumption for the underlying process of the intercept term we have the following state space framework, which can be estimated using maximum probability and a Kalman filter:

$$(r_{i,t} - r_{f,t}) = a_{i,t} + \beta_{i,t}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{1}$$

$$a_{i,t} = a_{i,t-1} + u_{i,t} \tag{2}$$

$$\beta_{i,t} = \beta_{i,t-1} + \eta_{i,t} \tag{3}$$

where $r_{i,t}$ is the return of the stock i at time t, $r_{m,t}$ is the return of the market portfolio, $r_{f,t}$ is the risk-free rate, and $\beta_{i,t}$ is the asset's non-diversifiable (systematic) risk in relation to the overall market risk at time t. $\varepsilon_{i,t}$ is an error term. Following existing work, we further assume the three error terms to be independent, homoscedastic, and serially uncorrelated:

$$\varepsilon_{i,t} \sim \text{MVN }(0,P),\ u_{i,t} \sim \text{MVN }(0,Q) \text{ and } \eta_{i,t} \sim \text{MVN }(0,K)$$

where P, Q, and K are covariance matrices. Departing from the initial state values, the Kalman filter provides recursive conditional estimates of the asset-specific state variables a and b for each time t up to T. The Kalman filter provides estimates of $\beta_{i,t}$ based on information available up to time t. Following Harvey (1990), we initialize the Kalman filter using arbitrary values for the state variables a and b and the corresponding covariance matrices (with large diagonal elements reflecting the uncertainty of the initial values)[4].

4. Results

4.1. Estimating Beta Using Static Models. Our analysis begins at a portfolio level. We estimate stock market betas, using the CAPM model, the Fama and French (1993) three factor model (hereinafter FF3), an augmented Fama and French (1993) three factor model with a momentum factor and the Fama and French (2015) five factor model (hereinafter FF5). We aim for a general overview of how stock market betas differ among cyclical and noncyclical industries, as well as of how stock market betas may vary under different asset pricing models. Subsequently, we shall replicate the analysis conditional on firm-level characteristics, macroeconomic and institutional factors.

Table 2 reports beta coefficients from time series regressions, for cyclical and noncyclical groups. Firms are classified into cyclical and noncyclical industries based on their industry codes. We employ monthly time series regressions for the period July 1990 to June 2018.

4 Repeated initializations with different values result in the series of state estimates not being sensitive to the choice of the initial values.

Table 2. **Estimates of systematic risk (beta coefficient)**

	cyclical	noncyclical
Beta (CAPM)	0.5037***	0.4175***
Beta (3FF model)	0.5344***	0.4358***
Beta (3FF model plus MOM)	0.5039***	0.4150***
Beta (5FF model)	0.4722***	0.3938***

The table reports beta coefficients from time series regressions, for cyclical and noncyclical groups. In the first row, the estimated beta coefficient is from the CAPM monthly time series regressions. Then, we re-estimate the beta coefficient based on monthly time series regression of the Fama-French factors (second row) and the Fama-French factors plus the Momentum factor (third row). Finally, we report beta estimates on monthly time series regression of the Fama-French five factor model. The sample period spans from July 1990 to June. The risk factors for our European stocks sample are obtained by Kenneth R. French website and AQR website. *,**,*** denotes statistical significance at the 10%, 5%, and 1% level respectively.

First, we observe that both cyclical and noncyclical industries exhibit statistically significant beta coefficients at 1% level for all the static asset pricing models incorporated. As expected, noncyclical industries exhibit lower market betas than cyclical industries. Furthermore, both types of industries exhibit small variations in beta coefficients conditional on the asset pricing model incorporated. This finding suggests that, the inclusion of additional systematic risk factors does not mitigate a firm's market risk.

Having established that market betas vary across cyclical and noncyclical industries, we further examine market betas variations conditional on firm-specific variables. We begin our analysis with a further classification based on Piotroski's (2000) fundamental strength, measured by FSCORE. Firms are first classified into cyclical and noncyclical industries. Then for each industry classification group, we form at the end of each June portfolios by sorting stocks based on FSCORE from the previous fiscal year. Firms are classified into Weak, MidScore, and Strong if a firm's Fscore is less than or equal to three, between four and six, or greater than or equal to seven, respectively.

Table 3 reports beta coefficients from monthly time series regressions, for cyclical and noncyclical groups, conditional on the FSCORE Classification.

Beta coefficients, in both industries increase when we further classify firms within each industry group into weak firms, middle firms and strong firms. However, we still observe lower market betas for noncyclical industries. This is an interesting finding yet to be expected. Different segments based on a firm-level variable should reveal new information about betas variations. In Table 2 this information is probably lost through aggregation.

A firm's fundamental strength is expected to influence market betas, since it is expected to capture the uncertainty associated with corporate income streams. Given that FSCORE's constituents are substitutes of the total variability of a firm's return on common equity, we argue that they represent both systematic and idiosyncratic components of risk and account at least for partial variation in systematic risk levels. Furthermore, since higher FSCORE values suggest strong fundamentals, we expect beta coefficients to be lower in strong FSCORE segment for cyclical firms. In respect to noncyclical firms, we do not expect large beta variations in terms of firms' fundamental strength.

Table 3. **Estimates of systematic risk (beta coefficient), conditional on Fscore Classification**

Panel A: Weak Fscore	**cyclical**	**Noncyclical**
Beta (CAPM)	0.7142***	0.6488***
Beta (3FF model)	0.7298***	0.6581***
Beta (3FF model plus MOM)	0.7294***	0.6551***
Beta (5FF model)	0.7195***	0.6477***
Panel B: Middle Fscore	**cyclical**	**Noncyclical**
Beta (CAPM)	0.7196***	0.5919***
Beta (3FF model)	0.7431***	0.6033***
Beta (3FF model plus MOM)	0.7431***	0.6043***
Beta (5FF model)	0.6671***	0.5699***
Panel C: Strong Fscore	**cyclical**	**Noncyclical**
Beta (CAPM)	0.7305***	0.6403***
Beta (3FF model)	0.7532***	0.6549***
Beta (3FF model plus MOM)	0.7519***	0.6565***
Beta (5FF model)	0.6710***	0.5798***

The table reports beta coefficients from monthly time series regressions, for cyclical and noncyclical groups, conditional on Fscore Classification. Firms are fist classified into cyclical and noncyclical industries. Then, for each industry classification group, we form at the end of each June portfolios by sorting stocks based on FSCORE from the previous fiscal. Firms are classified into Weak, MidScore, and Strong if a firm's Fscore is less than or equal to three, between four and six, or greater than or equal to seven, respectively. In the first row, the estimated beta coefficient comes from the CAPM monthly time series regressions. Next, we re-estimate the beta coefficient based on monthly time series regression of the Fama-French factors (second row) and the Fama-French factors plus the Momentum factor (third row). Finally, we report beta estimates on monthly time series regression of the Fama-French five factor model. The sample period spans from July 1990 to June. The risk factors for our European stocks sample are taken from Kenneth R. French website and AQR website. *,**,*** denotes statistical significance at the 10%, 5%, and 1% level respectively.

The results presented in Table 3 suggest that systematic risk levels increase as we move from the weak-firm segment to the strong-firm segment for cyclical industries. For noncyclical industries, we observe that beta coefficients of the weak-firm segment are similar to those of the strong-firm segment. FSCORE represents how investors assess and interpret the information contained in reported accounting figures. Given that it seems implausible that fundamentally strong firms may be considered riskier than fundamentally weak firms, our findings are likely to be consistent with the view that fundamental information is only gradually incorporated into prices by investors (Piotroski, 2000).

Finally, beta coefficients follow the same pattern as in Table 2 when we incorporate different asset pricing models. Both types of industries exhibit small variations in beta coefficients conditional on the asset pricing model incorporated.

Our final step, in respect to firm-level variables, is to examine whether lifecycle stages affect beta coefficient estimates in cyclical and noncyclical industries. Table 4 reports beta coefficients from monthly time series regressions, for cyclical and noncyclical groups, conditional on Lifecycle Classification. Firms are first classified into cyclical and noncyclical groups. Then, within each industry group, we form at the end of each June portfolios by sorting stocks based on LIFECYCLE rates from the previous fiscal year. A firm is classified as an Early Lifecycle stage firm if its lifecycle falls into the lowest-ranked quintile portfolio, and as a Mature Lifecycle stage firm, if its lifecycle falls into the highest-ranked quintile portfolios.

Table 4. **Estimates of systematic risk (beta coefficient), conditional on Lifecycle Classification**

Panel A: Growth	**cyclical**	**Noncyclical**
Beta (CAPM)	0.0333	0.0263
Beta (3FF model)	0.0183	0.0150
Beta (3FF model plus MOM)	0.0256	0.0222
Beta (5FF model)	-0.0054	-0.0007
Panel B: Maturity	**cyclical**	**Noncyclical**
Beta (CAPM)	0.0340	0.0224
Beta (3FF model)	0.0191	0.0105
Beta (3FF model plus MOM)	0.0249	0.0150
Beta (5FF model)	0.0002	-0.0050
Panel C: Decline	**cyclical**	**Noncyclical**
Beta (CAPM)	0.0298	0.0035
Beta (3FF model)	0.0166	-0.0044
Beta (3FF model plus MOM)	0.0208	-0.0005
Beta (5FF model)	-0.0051	-0.0305

The table reports beta coefficients from monthly time series regressions, for cyclical and noncyclical groups, conditional on Lifecycle Classification. Firms are first classified into cyclical and noncyclical groups. Then, for each industry group, we form at the end of each June portfolios by sorting stocks based on LIFECYCLE rates from the previous fiscal. A firm is classified as an Early Lifecycle stage firm, if its lifecycle falls into the lowest-ranked quintile portfolio and as a Mature Lifecycle stage firm, if its lifecycle falls into the highest-ranked quintile portfolios. In the first row, the estimated beta coefficient comes from the CAPM monthly time series regressions. Next, we re-estimate the beta coefficient based on monthly time series regression of the Fama-French factors (second row) and the Fama-French factors plus the Momentum factor (third row). Finally, we report beta estimates on monthly time series regression of the Fama-French five factor model. The sample period spans from July 1990 to June 2018. The risk factors for our European stocks sample are taken from Kenneth R. French website and AQR website. *,**,*** denotes statistical significance at the 10%, 5%, and 1% level respectively.

Market betas for both types of industries turn to be statistically insignificant across all asset pricing models suggesting that firm lifecycle stages do not provide any additional information on firms' beta variations[5].

Table 5 tabulates results of beta coefficients from monthly time series regressions, for cyclical and noncyclical groups, conditional on macroeconomic and institutional factors. We sort all countries in ascending order based on MACROEC values, and divide them into low (bottom 25%), medium (middle 50%), and high (top 25%) groups. The cut-off point for each group is based on the index values incorporated and the number of countries in each group. We use the same grouping method for all other country-level characteristics. Panel A reports beta coefficients of macroeconomic segments and Panel B reports beta coefficients of institutional segments for cyclical industries, while Panels C and D report beta coefficients for noncyclical industries.

5 Untabulated robustness test reveal that even we change LIFECYCLE cutoffs to 30-40-30 or even if we employ the age proxy suggested in Saravia et al (2020) and Chincarini et al. (2020), the results remain qualitatively unchanged.

Table 5. **Estimates of systematic risk (beta coefficient), conditional on macroeconomic and institutional factors**

	Panel A: Macroeconomic Factors - Cyclical Industries									
	MACROEC		BUSOPH		ANALYST		DVOL		TCOST	
	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH
Beta (CAPM)	0.6209***	0.5933***	0.6695***	0.5225***	0.6014***	0.5910***	0.5082***	0.4636***	0.5243***	0.5711***
Beta (3FF model)	0.6416***	0.6272***	0.6889***	0.5642***	0.6292***	0.6201***	0.5300***	0.4973***	0.5646***	0.6006***
Beta (3FF model plus MOM)	0.6457***	0.6278***	0.6939***	0.5614***	0.6335***	0.6212***	0.5334***	0.4992***	0.5620***	0.6041***
Beta (5FF model)	0.5556***	0.5179***	0.5651***	0.4890***	0.5663***	0.5076***	0.4525***	0.4185***	0.4670***	0.4881***

	Panel B: Institutional Factors - Cyclical Industries					
	INV PROT		PR		EM	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
Beta (CAPM)	0.5020***	0.4627***	0.7325***	0.6091***	0.4956***	0.5783***
Beta (3FF model)	0.5368***	0.4959***	0.7654***	0.6354***	0.5331***	0.6049***
Beta (3FF model plus MOM)	0.5342***	0.4978***	0.7663***	0.6383***	0.5344***	0.6093***
Beta (5FF model)	0.4609***	0.4515***	0.7405***	0.5495***	0.4710***	0.4821***

The table reports beta coefficients from monthly time series regressions, for cyclical and noncyclical groups, conditional on macroeconomic and institutional factors Classification. In the first row, the estimated beta coefficient comes from the CAPM monthly time series regressions. Then, we re-estimate the beta coefficient based on monthly time series regression of the Fama-French factors (second row) and the Fama-French factors plus the Momentum factor (third row). Finally, we report beta estimates on monthly time series regression of the Fama-French five factor model. The sample period spans from July 1990 to June 2018. The risk factors for our European stocks sample are obtained by Kenneth R. French website and AQR website. *,**,*** denotes statistical significance at the 10%, 5%, and 1% level respectively.

Table 5 **(continued)**

	Panel C: Macroeconomic Factors - Noncyclical Industries									
	MACROEC		**BUSOPH**		**ANALYST**		**DVOL**		**TCOST**	
	LOW	**HIGH**	**LOW**	**HIGH**	**LOW**	**HIGH**	**LOW**	**HIGH**	**LOW**	**HIGH**
Beta (CAPM)	0.5221***	0.4772***	0.6129***	0.4075***	0.5191***	0.5008***	0.4306***	0.3760***	0.4074***	0.4919***
Beta (3FF model)	0.5369***	0.5134***	0.6283***	0.4330***	0.5461***	0.5132***	0.4526***	0.4004***	0.4323***	0.5164***
Beta (3FF model plus MOM)	0.5412***	0.5118***	0.6343***	0.4335***	0.5520***	0.5149***	0.4561***	0.4021***	0.4324***	0.5220***
Beta (5FF model)	0.4626***	0.4380***	0.5221***	0.3939***	0.4190***	0.4878***	0.3549***	0.3704***	0.3880***	0.3875***
	Panel D: Institutional Factors - Noncyclical Industries									
	INV PROT		**PR**		**EM**					
	LOW	**HIGH**	**LOW**	**HIGH**	**LOW**	**HIGH**				
Beta (CAPM)	0.3963***	0.3796***	0.5704***	0.5374***	0.3831***	0.5198***				
Beta (3FF model)	0.4122***	0.4045***	0.5990***	0.5490***	0.4123***	0.5451***				
Beta (3FF model plus MOM)	0.4126***	0.4063***	0.6015***	0.5531***	0.4129***	0.5522***				
Beta (5FF model)	0.3751***	0.3684***	0.5875***	0.4842***	0.3842***	0.4122***				

Results for both types of industries are consistent with our expectations. Notably, systematic risk levels decrease in countries where economic stability, economic development and analysts' activity, as measured by MACROEC, BUSOPH and ANALYST, are high. In countries, where trading frictions are high (i.e. is low values of the DVOL variable and high values of the TCOST variable) betas increase. Countries with high investors protection (INV PROT) and low political risk (high values of PR) are characterized by lower systematic risk levels, while countries where managerial discretion over earnings is high exhibit increased systematic risk level.

In case of noncyclical industries, we observe the same patterns, but as anticipated, betas are of lower magnitude than the ones of cyclical industries. Thus, up to this point portfolio analysis' results are consistent with our formed hypotheses, conditional on macroeconomic and institutional factors.

4.2. Estimating Time-varying Systematic Risk Levels

In this subsection, we analyze fluctuations in Kalman filter betas in more detail. Table 6 presents the average yearly beta estimates and the corresponding standard deviations for the years 1990 to 2018, separately for each industry group. Time-varying market beta estimates do not alter our initial inference; that is, noncyclical industries exhibit lower systematic risk levels. Time-varying beta coefficients for cyclical industries span from approximately 0.20 to 0.75, while time-varying betas for noncyclical industries span from 0.10 to 0.60.

For both industry groups, stock market betas were relatively low in the early 1900s and increased notably at the beginning of the 2000s. They peaked during the first three years of the euro introduction and again from 2007 to 2009. In 2007, Ireland fell in a recession from Q2-Q3 2007. The eurozone recession dates from the first quarter of 2008 to the second quarter of 2009. These events are indeed beta-increasing events.

The table reports average annual beta coefficients for each sample year along with the respective standard deviations. Annual betas are calculated as the mean value of monthly Kalman filter estimates, from the CAPM, from the respective year. We provide results separately for each group (cyclical and noncyclical). The sample period spans from 1990 to 2018.

4.3. Determinants of Systematic Risk

Up to this point, our findings show variations in systematic risk levels between the two industry groups. Furthermore, systematic risk levels vary conditional on firm-level accounting fundamentals and over time. In this subsection, we address the question of which factors best explain the cross-sectional variation in systematic risk for both industry groups. We build a panel model of systematic risk, accounting for both cross-sectional and time series variation of betas. Specifically, we model betas as a function of firm-specific, macroeconomic and institutional variables, which we argue that influence beta on the cross-section. Formally, the estimated beta is modeled as:

$$\hat{\beta}_{i,t} = X_{i,t}\gamma + F_t\delta + I_i\varphi + \varepsilon_{i,t} \tag{4}$$

Where t describes the fiscal year-end month of firm i at year t, $\beta_{i,t}$ is the conditional estimate of beta from the Kalman filter for firm I at period t, $X_{i,t}$ is a vector of firm-level variables, F_t includes macroeconomic factors and I_i is a vector of institutional characteristics of the country where the firm is listed. The vectors γ, δ, ϕ and include the regression coefficients and $\varepsilon_{i,t}$ is the error term.

Table 6. **Dynamic beta estimates over the sample period**

	Cyclical		Noncyclical	
	Beta (CAPM)		Beta (CAPM)	
	β	SD	β	SD
1990	0.5351	0.0036	0.4379	0.0055
1991	0.3470	0.0128	0.2116	0.0133
1992	0.2002	0.0193	0.1065	0.0177
1993	0.2498	0.0225	0.1717	0.0209
1994	0.3147	0.0197	0.2572	0.0177
1995	0.1923	0.0238	0.1424	0.0221
1996	0.2180	0.0368	0.2046	0.0373
1997	0.2207	0.0299	0.2129	0.0261
1998	0.4067	0.0157	0.3506	0.0138
1999	0.4043	0.0228	0.2432	0.0235
2000	0.3848	0.0177	0.2257	0.0159
2001	0.6196	0.0139	0.4434	0.0123
2002	0.7286	0.0155	0.5342	0.0145
2003	0.7398	0.0139	0.6239	0.0135
2004	0.5913	0.0214	0.4516	0.0208
2005	0.6004	0.0238	0.4678	0.0224
2006	0.7145	0.0232	0.6341	0.0208
2007	0.6734	0.0257	0.6248	0.0230
2008	0.7432	0.0124	0.6319	0.0105
2009	0.6360	0.0093	0.5037	0.0090
2010	0.5138	0.0120	0.3866	0.0107
2011	0.5271	0.0121	0.4362	0.0113
2012	0.5497	0.0137	0.4802	0.0134
2013	0.5256	0.0184	0.5010	0.0167
2014	0.4599	0.0226	0.4388	0.0217
2015	0.5020	0.0214	0.4845	0.0185
2016	0.2877	0.0195	0.2407	0.0177
2017	0.4035	0.0250	0.3964	0.0235
2018	0.3917	0.0240	0.3826	0.0209

In Table 7 we provide regression results for the different factor sets, as well as the full model, and analyze the impact of each individual factor. Specifically, Table 6 presents yearly cross-sectional regression results for market beta determinants. We use the model in Eq. (4) together with the variables already defined to estimate the real determinants of beta. Cross-sectional regressions are estimated using OLS with clustered standard errors. Firms must have non-missing data on all firm-specific variables to be included in the initial regression sample. The sample period spans from 1990 to 2016.

We use dummy variables to indicate countries with high legal standards, high political risk and high managerial discretion over earnings. Index values for the investor protection index range from zero (weak investor legal protection) to 0.7759 (strong investor legal protection). Countries with investor protection index values above the median are defined as countries with strong investor legal protection. Index values for the political risk index range from 74.90 (high level of political risk) to 91.10 (low level of political risk). Countries with political risk index values above the median are defined as countries with low political risk. Earnings managements score varies from 5.10 (low managerial discretion over earnings) to 28.30 (high managerial discretion over earnings). Countries with earning managements values above the median are defined as countries with low managerial discretion over earnings.

Column (1) shows that there is a statistically significant impact of fundamentals' strength factor (FSCORE) on beta. For both types of industries, the relation is positive, highly statistically significant at the 1% level, a finding that contradicts with our H1 hypothesis but consistent with the portfolio analysis in subsection 4.1. In line with theoretical expectations, firms' fundamental strength indeed constitutes a source of corporate systematic risk, with an opposite relation than the expected. As previously mentioned, the unexpected positive relation between FSCORE and betas, is likely to be consistent with the view that fundamental information is only gradually being incorporated into prices by investors (Piotroski, 2000).

Finally, we also observe that firms' lifecycle stage is statistically insignificant for both industry groups. This finding is consistent with our previous findings based on a portfolio analysis[6]. Thus, H2 is rejected, since firms' LIFECYCLE does not seem to have an impact on betas.

Column (2) reports coefficient estimates for the set of macroeconomic factors. For cyclical industries, four out of five macroeconomic factors reveal a statistically significant impact on beta at 1% level. ANALYST is statistically significant at 10% level. Economic stability (MACROEC), economic development (BUSOPH) and analyst activity (ANALYST) are negatively related to betas as expected. Trading frictions, when proxied by DVOL are negatively related to betas. When trading frictions are proxied by TCOST, they are positively related to betas, consistent with our expectations as well.

For noncyclical industries, we observe the same patterns with lower in magnitude regression coefficients. Our results from column (2) validate our formulated hypotheses H3 - H5.

Column (3) reports coefficient estimates for the complete factor set, with the inclusion of institutional factors. Our findings on firm-level and macroeconomic variables remain unchanged. In line with our expectations, investor protection and political risk are negatively related to betas, while earning management is positively related to systematic risk levels, all statistically significant at 1% level. Both types of

6 It should be noted here that untabulated results using the age proxy suggested in Saravia et al (2020) and Chincarini et al. (2020) give qualitatively similar results to our LIFECYCLE proxy.

industries exhibit once more the same patterns, although regression coefficient is less in magnitude for noncyclical firms. Tabulated results validate hypotheses H6-H8.

Overall, regression results suggest that both industry groups' betas are affected by the same factors. However, in the case of noncyclical firms, factors' impact on systematic risk levels is of lower magnitude.

Table 7. **Determinants of systematic risk**

	Cyclical			NonCyclical		
	(1)	(2)	(3)	(1)	(2)	(3)
	Beta Coef.	Beta Coef.	Beta Coef.	Beta Coef.	Beta Coef.	Beta Coef.
FSCORE	0.0952***	0.0248***	0.0191***	0.0780***	0.0217***	0.0155***
LIFECYCLE	0.0000	0.0000	0.0000	0.0003	0.0000	-0.0002
MACROEC		-0.0041***	-0.0399***		-0.0035***	-0.0319***
BUSOPH		-0.0543***	-0.0443***		-0.0433***	-0.0352***
ANALYST		-0.0036*	-0.0068*		-0.0034***	-0.0023***
DVOL		-0.0362***	-0.0269***		-0.0242***	-0.0189***
TCOST		0.0532***	0.0139***		0.0477***	0.0148***
INV PROT			-0.0127***			-0.0108***
PR			-0.0355***			-0.0264***
EM			0.0624***			0.0518***

The table presents yearly cross-sectional regression results for market beta determinants. Monthly Kalman filter-estimated betas and annual accounting data are matched on a fiscal year-end basis. Market beta is modeled as a function of firm-specific, macroeconomic and institutional factors. We report average coefficient estimates. Annual panel regressions are estimated using OLS regressions with clustered s.e. Column (1) reports results on firm-specific variables, Column (2) reports average coefficient estimates on firm-specific and macroeconomic variables and Column (3) reports regression coefficients for the full model that includes firm-specific, macroeconomic and institutional variables. *,**,*** denotes statistical significance at the 10%, 5%, and 1% level respectively.

5. Conclusions. This paper analyzes stock market beta variability, in cyclical and noncyclical industries, using an integrated European market sample. We employ both static asset pricing models and Kalman filtering to obtain average betas and conditional beta estimates respectivelly. The latter are used in our cross-sectional regressions on the determinants of market betas.

Existing research on the topic is industry-specific, to the best of our knowledge. Thus, by analyzing systemic risk levels in cyclical and noncyclical industry groups and offering a general overview of beta activity between the two adverse groups, we contribute to the empirical literature.

Our findings confirm that in general noncyclical industries exhibit lower levels of systematic risk. However, for both industry groups the average stock market beta fluctuates considerably during the sample period. Kalman filter-based estimates show that, for cyclical industries, the average beta ranges between 0.20 and 0.75, while it stretches from 0.10 to 0.60 for noncyclical industries during the years of our sample period.

These results strongly suggest that correcting for time-variation in beta is key in the estimation of corporate risk levels. In particular, in the capital budgeting phase, depending on the constant beta of the OLS-based stock market and equity cost estimates, sub-optimal decisions will result.

Finally, we analyze the determinants of both industries' betas. Notably, we argue that firm-level fundamentals, as well as macroeconomic and institutional factors will affect stock market betas. Our cross-section results suggest that although noncyclical industries' market betas remain lower in size after the control of firms' fundamental strength, macroeconomic conditions and different institutional environments, both types of industries are equally affected by the variables incorporated in our study. Thus, we provide evidence that European cyclical and noncyclical groups of industries are more homogenous than expected.

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Appendix

Industry Classification

The table presents the classification of industries into cyclical and noncyclical. The industry code, the industry name and the percentage of participation of each industry in the total sample are included. The industry code and industry name are the ones provided by Worldscope and Datastream International.

Cyclical			Non Cyclical		
IND. GROUP CODE	INDUSTRY GROUP	% of Participation	IND. GROUP CODE	INDUSTRY GROUP	% of Participation
43	Industrial Machinery	6,99%	71	Food Products	15,21%
58	Software	6,44%	157	Biotechnology	12,25%
150	Computer Services	5,87%	95	Pharmaceuticals	9,52%
86	Business Support Svs.	4,78%	132	Medical Equipment	8,74%
30	Building Mat.& Fix.	3,89%	35	Farm Fish Plantation	5,62%
69	Clothing & Accessory	3,83%	59	Dur. Household Prod.	5,38%
57	Electronic Equipment	3,52%	169	Con. Electricity	4,99%
39	Heavy Construction	3,06%	88	Food Retail,Wholesale	4,60%
33	Specialty Chemicals	2,96%	45	Healthcare Providers	4,60%
84	Publishing	2,92%	96	Alt. Electricity	4,06%
115	Broadcast & Entertain	2,55%	142	Fixed Line Telecom.	3,82%
90	Specialty Retailers	2,49%	74	Renewable Energy Eq.	3,59%
50	Exploration & Prod.	2,35%	67	Brewers	3,43%
37	Electrical Equipment	2,25%	103	Medical Supplies	3,28%
41	Media Agencies	2,23%	47	Waste, Disposal Svs.	2,57%
126	Telecom. Equipment	1,74%	144	Water	2,42%
64	Transport Services	1,62%	114	Soft Drinks	1,79%
51	Oil Equip. & Services	1,52%	91	Multiutilities	1,48%
55	Recreational Services	1,52%	44	Defense	1,17%
63	Auto Parts	1,50%	79	Tobacco	0,70%
122	General Mining	1,38%	120	Drug Retailers	0,55%
99	Marine Transportation	1,32%	52	Pipelines	0,23%
56	Iron & Steel	1,30%			
151	Internet	1,30%			
101	Divers. Industrials	1,26%			
117	Comm. Vehicles,Trucks	1,26%			
66	Apparel Retailers	1,24%			
60	Furnishings	1,21%			
130	Semiconductors	1,21%			
34	Computer Hardware	1,19%			
134	Bus.Train & Employmnt	1,13%			
100	Gambling	1,13%			
72	Restaurants & Bars	1,13%			
70	Containers & Package	0,99%			
87	Broadline Retailers	0,95%			
36	Home Construction	0,95%			

Appendix (continued)

Cyclical			Non Cyclical		
IND. GROUP CODE	INDUSTRY GROUP	% of Participation	IND. GROUP CODE	INDUSTRY GROUP	% of Participation
94	Travel & Tourism	0,95%			
80	Hotels	0,93%			
82	Paper	0,91%			
32	Industrial Suppliers	0,91%			
119	Gold Mining	0,79%			
68	Distillers & Vintners	0,77%			
143	Mobile Telecom.	0,75%			
48	Personal Products	0,73%			
98	Aerospace	0,69%			
92	Commodity Chemicals	0,69%			
54	Nonferrous Metals	0,63%			
155	Recreational Products	0,63%			
61	Toys	0,61%			
75	Consumer Electronics	0,57%			
65	Automobiles	0,55%			
62	Nondur.Household Prod	0,55%			
129	Airlines	0,53%			
83	Alternative Fuels	0,51%			
85	Home Improvement Ret.	0,51%			
97	Integrated Oil & Gas	0,45%			
40	Delivery Services	0,36%			
156	Spec.Consumer Service	0,34%			
93	Aluminum	0,34%			
46	Financial Admin.	0,34%			
49	Coal	0,34%			
131	Trucking	0,28%			
38	Forestry	0,24%			
31	Gas Distribution	0,24%			
53	Tires	0,20%			
153	Footwear	0,18%			
89	Diamonds & Gemstones	0,16%			
81	Railroads	0,14%			
78	Plat.& Precious Metal	0,14%			
105	Elec. Office Equip.	0,08%			