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Evolving character of the CAPM beta – the case of the telecom industry

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Executive summary

Assessment of a company's risk is an important part of an investment making decision process. However, in the case of regulated companies the correct judgment of risk is particularly important. Profitability and customers' prices in the regulated sector depend directly on a regulator's view of risk. Errors made at the time of the review can impact strongly on the market. In this short study I address the current risk of the telecommunications sector. The e-commerce bubble of the late 1990s brought about a dramatic change in the stock market's composition. The telecoms industry, which is a significant part of the 'high-tech' industry, experienced remarkable changes in its systematic risk (as measured by the CAPM (equity) beta). Using data for 17 telecom companies (11 European and 6 non-European) over the period of January 1998 to March 2003 I document these changes. In the last four years three sub-periods can be distinguished: a pre-bubble period of low equity betas, a bubble period with higher values, and then a subsequent post-bubble decline in market risk. This pattern is not that strong when asset betas are considered, i.e., once changes in the level of gearing ratio are taken into account the pattern of risk is much smoother. Moreover, the current level of average asset betas is similar, or even lower, than the pre-bubble level.

Keywords: market risk, CAPM, Kalman filter, telecommunication sector

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1. Equity betas

1.1. Methodology

The theoretical work of Harry Markowitz in the early 1950s formed a basis for the relationship between returns and risk that is commonly tested in the form of the market model:

$$R_t = \alpha + \beta R_{M,t} + \varepsilon_t \tag{1}$$

The capital asset pricing theory specification is:

$$R_t - R_{f,t} = \beta (R_{M,t} - R_{f,t}) + \varepsilon_t , \tag{2}$$

and the so-called empirical form of the capital asset pricing theory specification is:

$$R_t - R_{f,t} = \alpha + \beta (R_{M,t} - R_{f,t}) + \varepsilon_t , \tag{3}$$

where

R_t – denotes the return on the company's asset at time *t*,

$R_{M,t}$ – is the return on the market portfolio at time *t*,

$R_{f,t}$ – refers to the risk free rate of interest at time *t*.

Over the years the debate concerning whether the market portfolio is sufficient to explain the returns of individual securities led to the development of models that enrich the above equations by additional factors (e.g., Sharpe (1970), Sharpe et al. (1995), Fama and French (1992, 1993 1996) and many others) and the derivation of an alternative approach based on the concept of zero-beta portfolio (e.g., Ross (1976) and numerous papers that followed seeking to define common economic factors).

Although there are now many models of the return-generating process, one of the above specifications (i.e., equations (1)-(3)) is still most commonly used to estimate beta to assess a security's expected rate of return for the purpose of discounting cash flows.[2] Unfortunately, these models are not free from estimation problems. For example, problems arise when returns come from a non-normal distribution and/or are serially correlated. Such violations of the OLS assumptions lead to inefficient estimates. Moreover, the regression specifications in equations (1)-(3) impose that the model parameters, i.e., the beta and the intercept terms (in equations (1) and (3)), are constant over the period in question. Many empirical studies document that these parameters are not constant over time, (e.g., Blume (1971, 1975, 1979), Fabozzi and Francis (1978), Sunder (1980), Clarkson and Thompson (1990)). This indicates that the length of a regression window is important and is likely to affect the results. Unfortunately, there is no theory which helps to determine the optimal length of the regression window, or if time-varying characterisation of the parameters is allowed, the nature of this pattern. Numerous studies reach the conclusion that the betas tend to regress towards the mean. In other words, high beta stocks tend to decline over time towards unity, while low beta stocks tend to increase towards unity over time. Because all the betas are estimated with some error, this means that high (low) estimated betas tend to be overestimated (underestimated). Therefore, some adjustment towards the market mean value of one seems

[2] Alternative models of assets pricing do not have clear advantages over the traditional CAPM specification. Although the empirical evidence for CAPM is mixed, the other models are not faultless either. Moreover, the extension of CAPM by Fama and French (1992) is not uniformly supported by empirical evidence, and is not backed-up by any convincing theoretical argument. For the evidence on a weak explanatory power of the Fama-French 3 Factor model see, for example, Campbell (2001), Dimson et al (2001), Siegel (1998) and Grout and Zalewska (2003).

appropriate. Different types of Bayesian adjustment have been proposed (e.g., Kryzanowski and Jalilvand (1983), Gombola and Kahl (1990)) and the alternative approach of Vasicek has proved popular.

Even the most accurate adjustment does not address the question of how the beta evolves over time. The need to detect the time-pattern of the market risk has inspired many empirical studies and the last decade has brought significant progress in the development of econometric techniques that enable the estimation of the time pattern of market risk. In this paper I use an approach based on the Kalman filter (KF), stemming from Black et al. (1992). To achieve a better fit than my forerunners I also allow for the time-varying character of the constant term (i.e., CAPM's α). A generalised autoregressive conditional heteroskedasticity (GARCH) specification of the error term is also introduced to the model.

Specifically, to trace the changes in the market risk over time and address the issue of serial correlation of volatility of stock market returns, I use the market model specification (equation 1) with a GARCH(1,1) specification of the error term. The Kalman filter is employed to estimate the GARCH effects and the time paths of the market model coefficients.[3] More precisely, I assume that at any time t the return on asset i, R_{it}, can be explained by the return on the market portfolio R_{Mt}:

$$R_{it} = \alpha_t + \beta_t R_{Mt} + \varepsilon_t \ , \tag{4}$$

where the error generating process $\varepsilon_t \sim N(0, \sigma_t^2)$ has a variance described as:

$$\sigma_t^2 = \theta_0 + \theta_1 \sigma_{t-1}^2 + \theta_2 \varepsilon_{t-1}^2 . \tag{5}$$

The time-varying coefficients, α_t and β_t constitute a state vector in the state-space representation of the Kalman Filter. Denoting the value of the state vector at time *t* by a_t (i.e., $a_t = [\alpha_t, \beta_t]'$), I complete the state-space model by defining the state equation as

$$a_t = a_{t-1} + \eta_t \ , \tag{6}$$

where η_t is a 2x1 vector of serially uncorrelated disturbances with zero mean and covariance matrix *Q*. [4] In the later part of the paper I refer to this estimation model as KF.

The decision to use the market model, rather than capital asset pricing specifications, stems from the fact that it avoids having to choose a risk-free asset. Although the theoretical concept of the risk-free asset is intuitively clear, the practical choice of an asset that is truly risk-free is less obvious. Bruner (2003) quotes that 3, 5, 10 or longer Treasury notes are often used by practitioners as a proxy for the risk-free rate of return, whereas textbooks advise using Treasury-bills. The tendency to use medium- or long-term T-bonds is motivated by the desire to match the company's investment horizon with the maturity of debt. However, in the current

[3] We also tested for a stochastic time trend but do not report it in the paper since it was not detected. The results can be obtained from the author on request.

[4] In fact, in order to express the above system in the state-space representation of the Kalman Filter the state vector should have three elements: the two already mentioned stochastic parameter of the measurement equation (i.e., α_t and β_t) and a deterministic element to represent the variance of the error term,σt2. To conduct the calculations I adopt the technique (and the programme) of parameter estimation introduced in Zalewska-Mitura and Hall (1999). However, to keep the notation transparent I present the state vector as a vector of stochastic variables only.

analysis of the telecoms industry where a big part of our sample period coincides with the e-commerce bubble, such a strategy might not be best. In addition daily fluctuations of yields that proxy the risk free rate of return are known to have stochastic properties that are inconsistent with the assumption of the CAPM on the risk free rate of return. Therefore, the decision to 'play safe' and sidestep these problems by using the market model specification seem reasonable.[5]

The other question that must be answered concerns data frequency, i.e., whether the returns used for estimations should be daily, weekly, or monthly. If it is true that individual stock returns are serially uncorrelated and the relation between market returns and individual stock returns are the same for different frequency of returns (i.e., daily, weekly and monthly) then the highest frequency data, i.e., daily, should be used for the regression analysis. It would guarantee smaller standard errors of the estimated values.[6] The evidence of whether these above-mentioned assumptions are correct is mixed but it is commonly agreed that the problems of autocorrelation and heteroscedasticity should be solved by using more sophisticated econometric techniques rather than lowering the frequency of the data. However, lower frequency data is often used especially when the market risk is estimated for big groups of companies. For instance, London Business School's estimates of betas are based on monthly returns for a period of five years. Bloomberg use weekly observations for the period of two years to calculate their betas.[7] Using a smaller time window allows Bloomberg's estimates to better capture market trends that could disappear in five-year windows.

For the purpose of this study monthly returns were unsuitable. This is because there would not be enough data points to estimate time-paths (several companies included in our sample have less than 50 monthly observations available). Using weekly returns would be an alternative only if the weekly time series manifested more 'normal' properties than the daily series. Unfortunately, it was not true in the case of our sample. Therefore, the daily frequency was chosen.

1.2. Sample selection

Following the UK many governments have adopted a privatisation policy. With the exception of the privatisation undertaken by post-communist countries, telecommunications companies have typically been amongst the first companies to change ownership. Therefore, the number of candidates for my study ought to be sufficiently large. Although there are many telecoms companies listed, some of them only became public after 1999 (e.g., Swisscom of Switzerland, Telenor of Norway, etc.). These companies, for obvious reasons, are not suitable for examining the movement of beta over the period of the e-commerce bubble. To cover the period of the e-commerce bubble, I decided that the sample should start at least in 1998. This limited me to 11 companies (listed on developed stock exchanges) for which daily returns over the period between 1 January 1998 and 14 March 2003 were available.[8] For illustration purposes I divided the sample into two subgroups. Eight companies were used to create a 'European' sub-sample and three companies, one from Japan, one from New

[5] In addition Campbell et al. (1997) stress superiority of the market model, and in general, statistical model over economic models in event studies.

[6] The estimated values of coefficients are unaffected by the data frequency (the estimator is unbiased).

[7] The other difference between these two approaches is that LBS uses Vasicek adjustment, whereas Bloomberg uses Blume adjustment.

[8] For the Danish company TDC results are presented since 28 January 1999 because the data for the market index on the local stock exchange provided by DataStream start on that day.

Zealand and one from Australia, created the other 'non-European' sub-sample. The list of companies selected for my comparison, the codes I used to refer to the company, the names of the market indices used in the corresponding regressions and their countries of origin are presented in Table 1.

Table 1. Selected telecommunications companies

	Company name	Code	Market index	Country of origin
European	TDC	TDC-DNM	Copenhagen KFMX	Denmark
	British Telecom	BT-UK	FTSE ALL SHARE	England
	France Telecom	FT-FRN	CAC 40	France
	Deutsche Telekom	DT-GRM	DAX 30	Germany
	Telecom Italia	TI-ITL	Milan MIBTEL	Italy
	KPN	KPN-NL	AEX	Netherlands
	PT Telecom	PT-PRT	DAX 30	Portugal
	Telefonica	TLF-SPN	Madrid SE General	Spain
Non-European	Telstra Corporation	TST-AST	ASX ALL	Australia
	NPN Telegraph & Telephone	NPN-JPN	NIKKEI 225 Stock Average	Japan
	Telecom Corp. of New Zealand	TC-NZ	New Zealand SE All	New Zealand

To provide a better assessment of the current market situation I have created a larger sample of 17 telecom companies. Of these 14 came from developed markets and 3 from emerging markets. The 'Developed' sample consists of companies already classified as 'European' and 'non-European', plus telecoms companies originating from Austria, Norway and Switzerland. These additional three companies are not included into the 'European' sample due to their short listing. The other sample, called 'Emerging', consists of three companies. Due to data availability problem there are only three. I wanted the 'Emerging' sample to match my 'Developed' sample by geographical location therefore companies listed on the emerging markets of Europe as well as Asia/Indonesia were primarily considered. However, information on net debt was available only for the three companies finally included in the 'Emerging' sample (necessary to make possible the calculations of asset betas).

Table 2 presents the list of companies included in the extended sample, as well as their respective codes used, the stock market indices used in the corresponding regressions and the countries of origin.

Table 2. Extended sample of telecommunications companies

	Company name	Code	Market index	Country of origin
Developed	Telstra Corporation	TST-AST	ASX ALL	Australia
	Telecom Austria	TLK-AUS	Austrian Traded Index	Austria
	TDC	TDC-DNM	Copenhagen KFMX	Denmark
	British Telecom	BT-UK	FTSE ALL SHARE	England
	France Telecom	FT-FRN	CAC 40	France
	Deutsche Telekom	DT-GRM	DAX 30	Germany
	Telecom Italia	TI-ITL	Milan MIBTEL	Italy
	NPN Telegraph & Telephone	NPN-JPN	NIKKEI 225 Stock Average	Japan
	KPN	KPN-NL	AEX	Netherlands
	Telecom Corp. of New Zealand	TC-NZ	New Zealand SE All	New Zealand
	Telenor	TNR-NRW	Oslo Exchange All Share Index	Norway
	PT Telecom	PT-PRT	DAX 30	Portugal
	Telefonica	TLF-SPN	Madrid SE General	Spain
	Swisscom	SWC-SWT	Swiss Market	Switzerland
Emerging	Telecom Malaysia	TLM-MLS	DJWI Malaysia	Malaysia
	Tecom	TCM-TWN	Taiwan SE 100	Taiwan
	Telecom Asia	TLA-THL	DJWI Thailand	Thailand

1.3. Regression results

In order to see the full picture of changes in market risk and the advantage of the time-varying (KF) approach over the traditional time-invariant approach I compare betas obtained for all the time series using both techniques (see Appendix 1). Each graph plotted in the appendix shows the time path of the beta coefficient obtained from KF (a blue line) and the value of the beta obtained from the OLS regression (a pink line).[9] I do not present time-paths of intercepts obtained from KF and OLS regressions since none were significantly different from zero at the 95% level. It is important to note that the OLS values are crude estimates, i.e., without any adjustment. This is because the time pattern, rather than the best adjustment of time-invariant estimates, is the main concern of this study. Appendices 2 and 3 present estimates of GARCH(1,1) effects and details of the OLS regressions respectively.

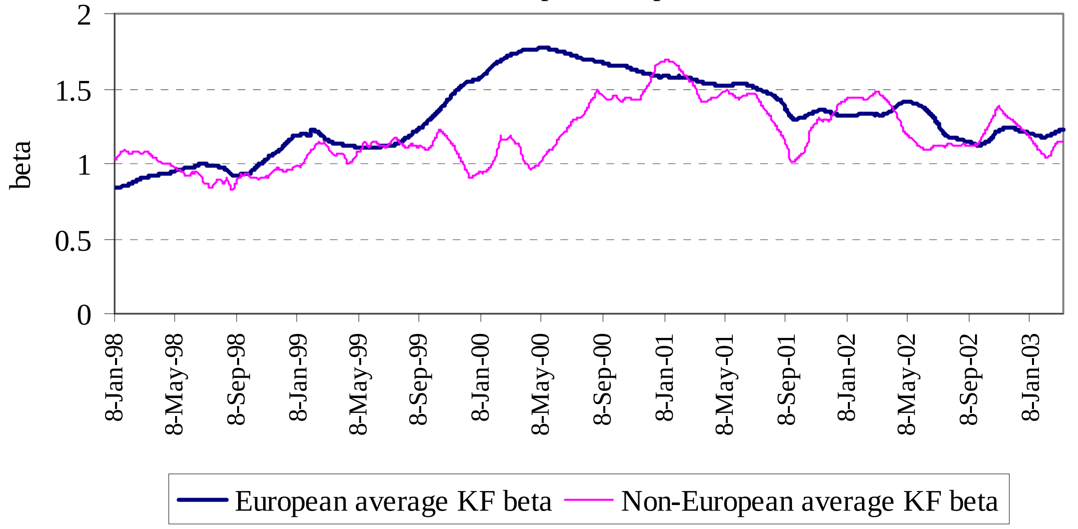
It is clear that the individual time paths of the beta coefficients exhibit a similar pattern and that this is far from constant over time: the middle part of the period in question is characterised by higher values of beta than the beginning and the end of the sample. Moreover, companies listed on emerging markets seem to manifest higher volatility of market risk. This observation is very interesting, because the high volatility of market risk in the case of emerging markets may be one of the reasons why traditional time-invariant estimates of market betas are believed to give poor results.

[9] OLS regressions are traditional regressions as described by equation (1). However, Newey-West correction was used to deal with the possible presence of heteroscedasticity and autocorrelation.

To abstract from individual company effects Figures 1-2 present several equally weighted averages of time-varying and time-invariant estimates of the betas.[10] Figure 1a presents time-varying KF equally weighted paths calculated for the eight European and three non-European companies as listed in Table 1. The similarity of the pattern is striking although the non-European sample consists of only three companies (the individual effect of high fluctuations observed for TC-NZ is not fully diversified away). Figure 1b compares equally weighted averages of betas estimated for companies listed on developed markets and emerging markets as listed in Table 2. It is clear that market risk on emerging markets is more volatile than on developed markets. However, the average level of market risk of telecoms companies listed on emerging markets is comparable with the average market risk of companies listed on developed markets. The e-commerce bubble increased the market risk of telecoms companies on both developed and emerging markets. Figures 2a and 2b document clearly that the betas of both groups were above the long-term average during the e-commerce bubble.

Finally, Figure 2c plots an equally weighted average of time-varying KF betas and an equally weighted average of time-invariant OLS betas obtained for all companies listed in Table 2. It is apparent that since 2001 there is a slow but persistent decline in market risk of the telecom companies. It is interesting to note that all but one of the spikes observed on the average of KF time-paths estimated for the emerging markets disappears when the average over all companies was taken. This sharp and short-lived decline (a downward spike) of market risk coincides with high market fluctuations following the terrorist attack of 11 September 2001.

Figure 1a. Comparison of average KF betas estimated for the European and the Non-European samples



[10] I use equally weighted, not value weighted, averages to avoid putting too much significance on the time-paths obtained for the few biggest companies (e.g., BT-UK and DT-GRM). In addition, in this way I avoid introducing daily fluctuations of exchange rates in our analysis (the companies are quoted in different currencies).

Figure 1b. Comparison of average KF betas for the Developed and the Emerging samples

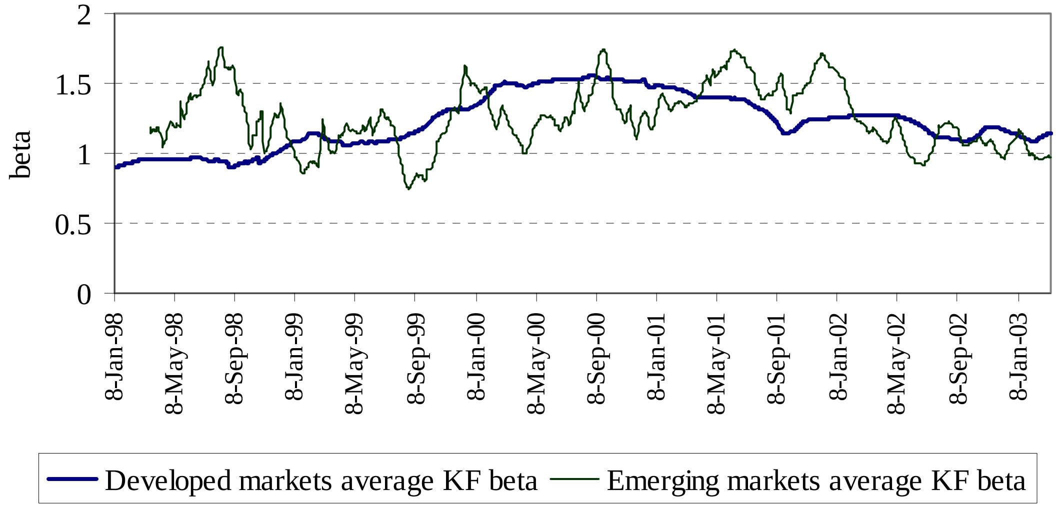


Figure 2a. Comparison of the average KF and OLS betas calculated for the joint European and Non-European samples

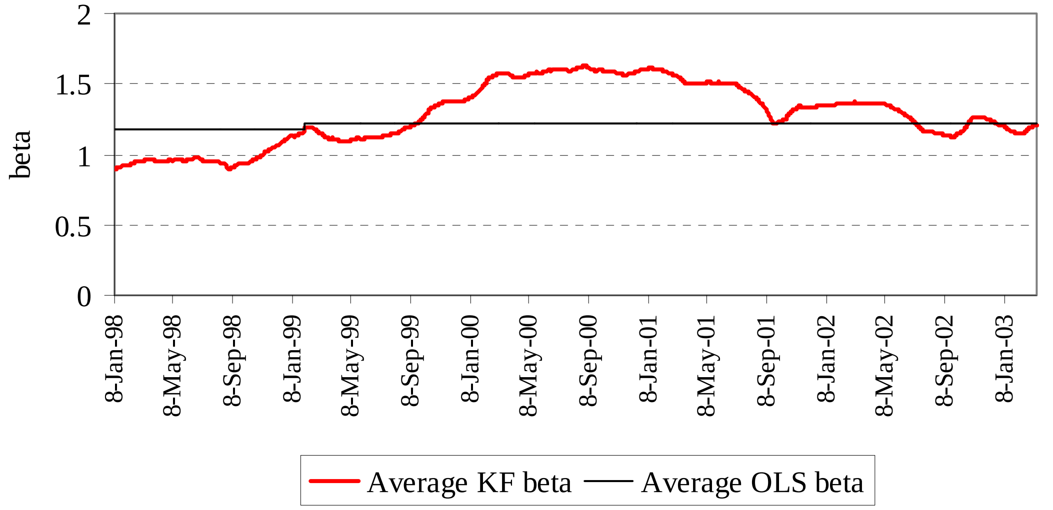


Figure 2b. Comparison of the average KF and OLS betas estimated for the Emerging sample

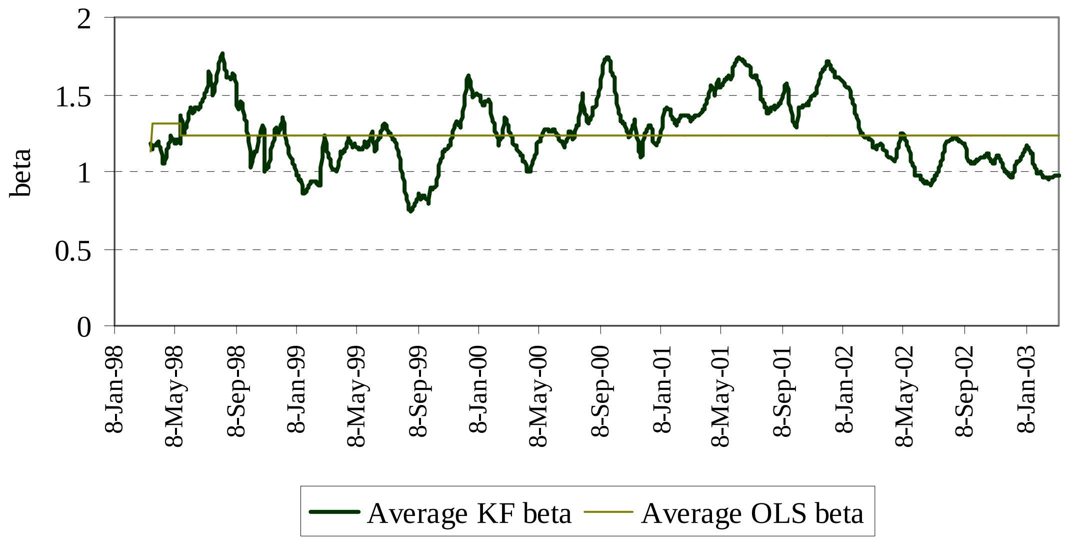
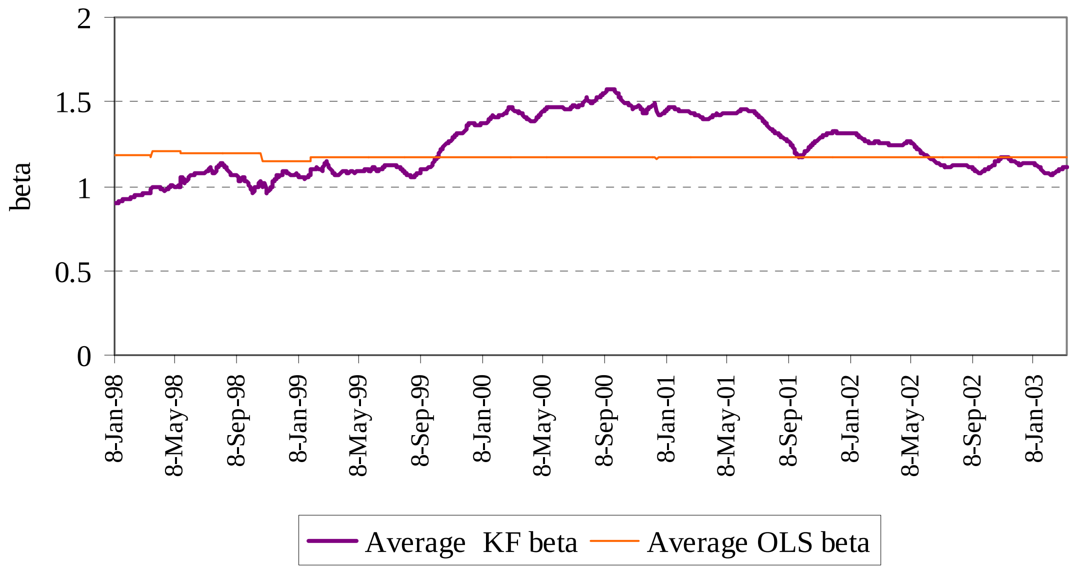


Figure 2c. Comparison of KF and OLS betas estimated for all companies



2. Asset betas

The change in the company's debt structure is one of the key factors that impacts on how investors assess a company's risk. Therefore for comparative purposes the beta, which from now on will be referred to as equity beta, ought to be adjusted for differences in debt. The adjusted beta is called the asset beta.

2.1. Methodology

There are two alternative methods of calculating asset betas, depending on the process by which debt affects the cost of capital. The most commonly used adjustment is based on incorporating the gearing level into equity betas. The alternative approach (not discussed in this paper due to the lack of data required for its application) takes into account the corporate tax and the proportion of shareholders that are eligible for imputation tax credits.

For the purpose of my analysis asset beta[11], β_a, is defined as

$$\beta_a = (1 - g)\beta, \tag{7}$$

where β refers to the equity beta and g is a net gearing ratio defined as:

$$g = \frac{net\ debt}{net\ debt + market\ value\ of\ equity}.$$

In other words,

$$\beta_a = \frac{market\ value\ of\ equity}{net\ debt + market\ value\ of\ equity}\beta.$$

Although the definition is straightforward its implementation is not. The first problem arises from the fact that the gearing ratio g is not constant over time. It is not only that the value of net debt changes over time, but also the market value of equities is far from constant. The second problem stems from the fact that the equity beta also has a time-varying character. Even in the traditional time-invariant approach to the estimation of market risk, the question of matching the length of a window for the equity beta estimate to the period when the gearing ratio is constant is not a trivial one. In the case of time-varying estimates of market risk the correct assessment of companies' net gearing is even more complicated.

2.2. Empirical evidence

Appendix 4 presents gearing ratios calculated on the day when the data on the net debt and market value were provided by DataStream. High variations in the gearing ratios over time and across companies are apparent. However, a comparison among different groups of companies is complicated by the fact that tax-years in different regions start on different days. Therefore, the data relate to different periods in different countries. To deal with the problem we assume that December and the following March data refer to the same period and we use them to calculate averages for a particular year. The grouping in the case of Australia and New Zealand is more ambiguous, because statistics for these two countries are available on 31 June, i.e., half year across a tax year in Europe. However, because they are closer to the March statistics that are already averaged with the December statistics of the previous year,

[11] I assume that risk of debt is zero.

rather than the end of year statistics, I add them to previous year's December numbers to calculate averages. Each bar in Figure 3a is an average of the December statistics for continental countries and a following year March statistics for the BT-UK. Figures 3b and 3c present averages for December (say 1999), and March and June of the following year (i.e., 2000).

Figures 3a, 3b and 3c display a similar pattern for companies listed on developed markets. For both the European and non-European companies we observe an initial decline and then a sharp increase in the gearing ratios. Post e-commerce bubble gearing ratios are at least twice the pre-bubble values, and as much as four to five times the gearing ratios of the bubble period for the European companies. In the case of emerging markets the average gearing ratio seems more stable. The Emerging sample, in contrast to the Developed sample, is not characterised by the decrease in the gearing ratio during the bubble. Moreover, in years 1998 and 1999 gearing ratios in emerging markets were higher than on developed markets. This pattern was reverseed after 2000.

Figure 3a.Comparison of average gearing ratios for European and Developed European samples

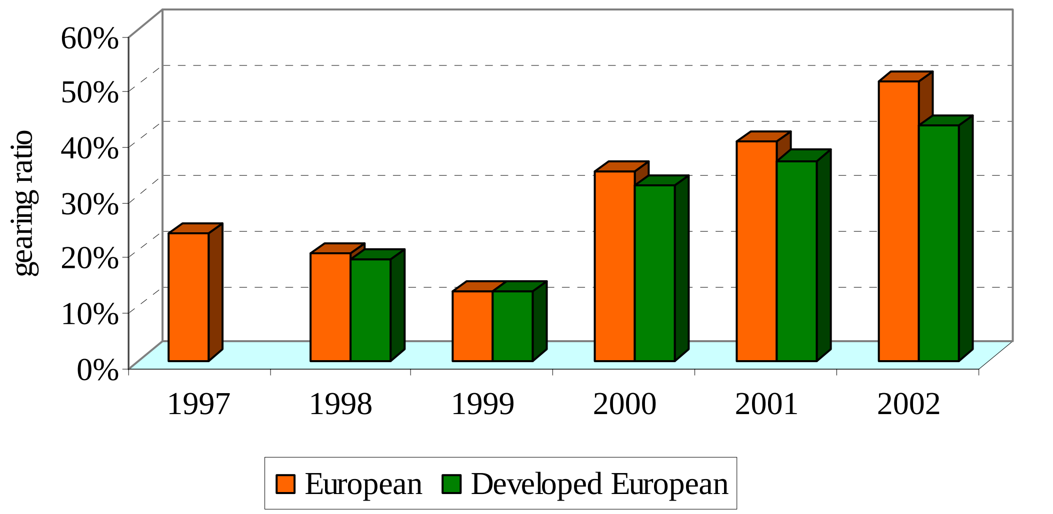


Figure 3b. Comparison of gearing ratios for Developed Non-European and Emerging samples

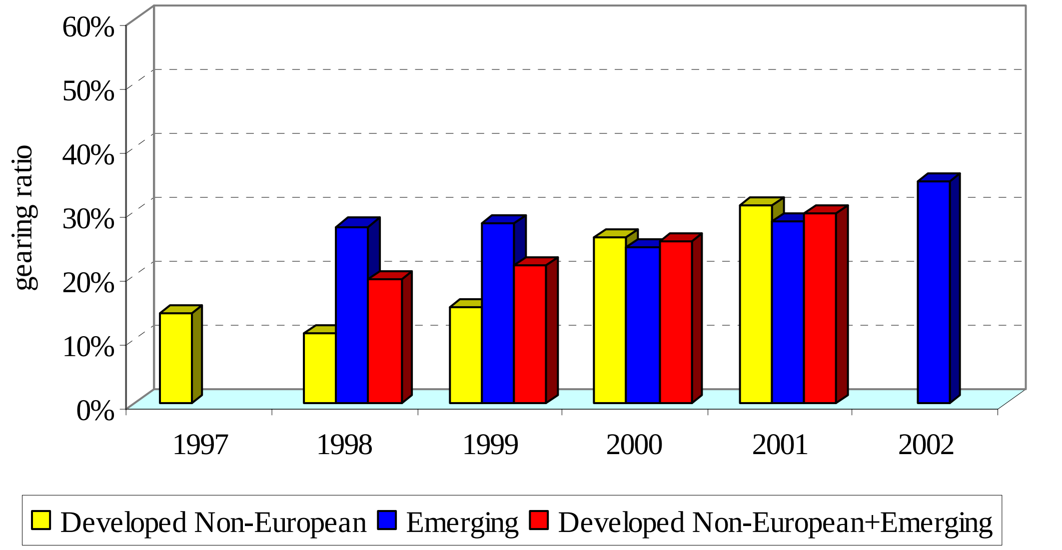
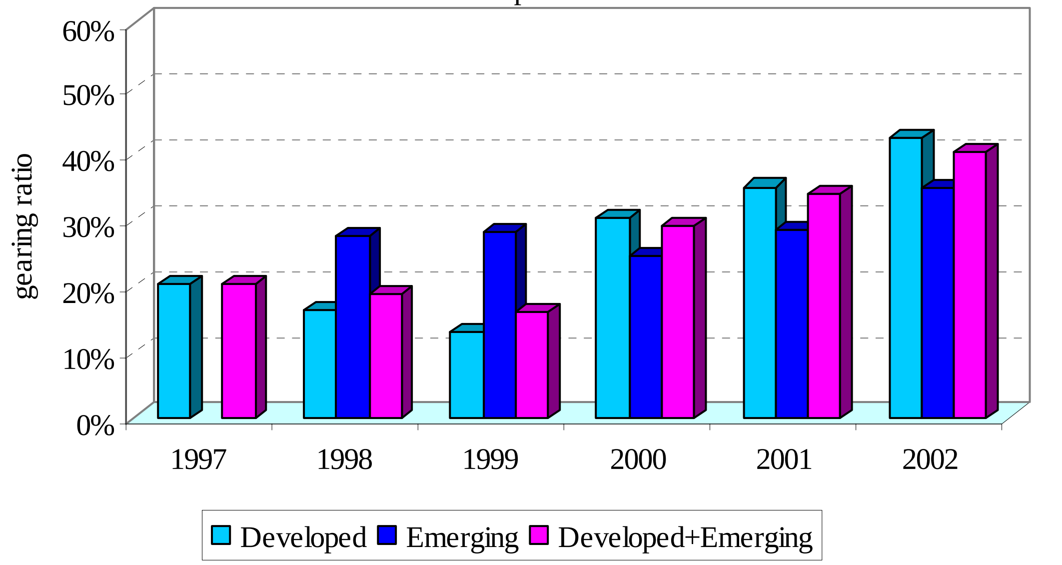


Figure 3c. Comparison of gearing ratios for Developed and Emerging samples



In order to adjust the time-paths of the equity betas (i.e., to implement equation (7)) I calculated discrete time-paths of gearing ratios for each company. Because companies' gearing ratios are calculated annually, each particular value is assumed to hold six months before and six months after it is stated in Appendix 4. In the cases when information about the most recent values was not available, the last available figure was used. In the case of TC-NZ when the reporting was moved from 31 March to 30 June between 1999 and 2000 the two month gap was equally divided and filled in by the 1999 and 2000 figures.

Figures 4a and 4b compare the average equity and the average asset betas for different groups of companies. In Figure 4a, European and non-European companies average equity and asset betas are plotted. This figure reveals that the similarity between European and non-European equity betas extends to asset betas. However, due to the fact that gearing ratios of non-European companies are lower than corresponding figures for the European companies, the time-path of asset betas of the non-European sample lies marginally above the time-path of the average asset beta of the European sample. The level of market risk remains practically unchanged when the group of European companies is enlarged by three additional entries, i.e., TLK-AUS, TNR-NRW and SWC-SWT. Figure 4b shows the equity and asset betas for the Developed and the Emerging samples. As expected, the higher average gearing ratios for the Emerging sample in 1998 and1999 and lower in the period between 2000 and 2002 compared with the Developed sample (see, Figure 3c) reverse the mutual position of the asset betas of Emerging and of Developed markets. The initially higher asset betas of the Emerging sample become lower than the asset betas of the Developed sample after 2000.

Finally, Figure 5 compares the average equity, the average asset betas and corresponding standard deviations calculated at each point in time for all companies. It is important to note that although the post-bubble equity betas are marginally higher than the betas estimated for the pre-bubble period, the asset betas manifest a reversed pattern. It is also interesting that over time differences between asset betas of individual companies became smaller than differences of corresponding equity betas (the standard deviation of the asset betas is currently smaller than the standard deviation of the equity betas).

Figure 4a. Comparison of equity and asset KF betas for the European and the Non-European Samples

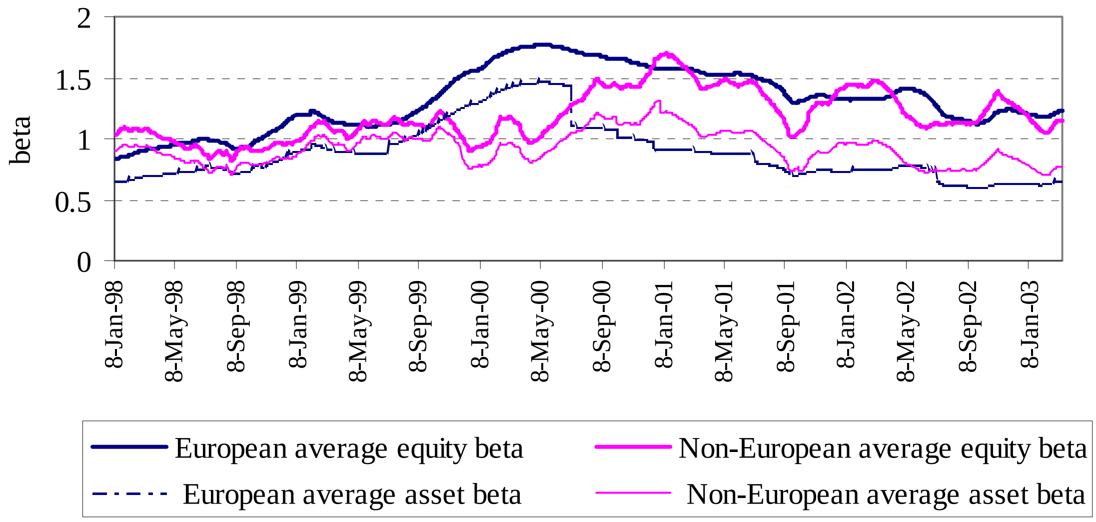


Figure 4b. Comparison of equity and asset KF betas for the Emerging and the Developed samples

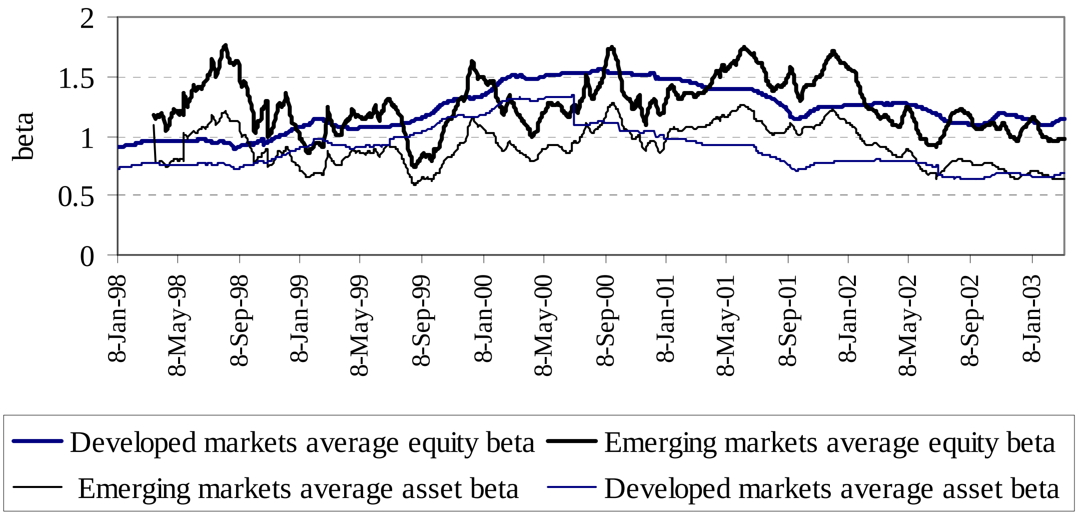
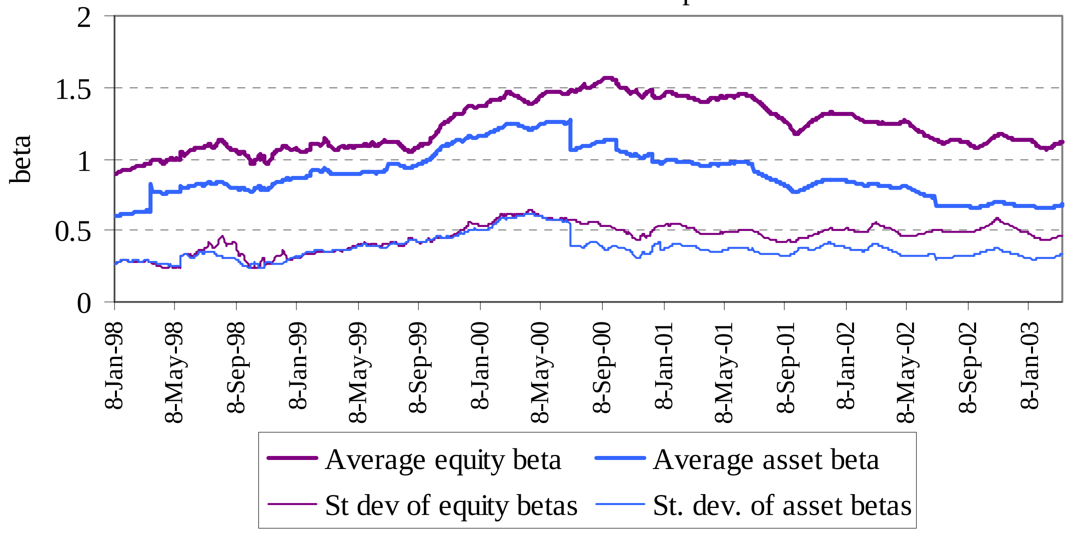


Figure 5.Comparison of equity and asset KF betas and corresponding standard deviations for all companies



The gearing adjustment also requires a word of comment. The widening gap between the sample average equity beta and the asset beta is the result of a drop in share prices not a dramatic increase in net debt. Since 2001 a negative growth rate of net debt in many companies can be observed. For instance, the following growth rates can be calculated based on data provided by DataStream for 2001 and 2002: -50% for BT-UK, -22% for KPN-NL, and –1% in the case of NPN-JPN and TST-AST, 0.5% for TC-NZ and 7.2% in the case of FT-FRN (no inflation adjustment was taken into account). Therefore, the high increase in the gearing ratios can be fully attributed to the decline in corresponding share prices.

3. Conclusions

The analysis of a trend in the equity and the asset betas of selected telecoms companies is the main concern of this study. I document a considerable increase in equity betas during the e-commerce bubble both for developed European and non-European markets represented here by Japan, Australia and New Zealand. The equity betas have been in decline since 2000. Also a similar trend is observed in the case of the selected emerging markets, although the estimated equity betas have a more volatile character than the betas estimated for the developed markets. Finally, the calculations indicate that the current level of asset betas for the telecoms industry is below its pre-bubble values. I argue that the decline in asset betas during the last two years is mostly due to the steady decline in share prices, not the increase in net debt.

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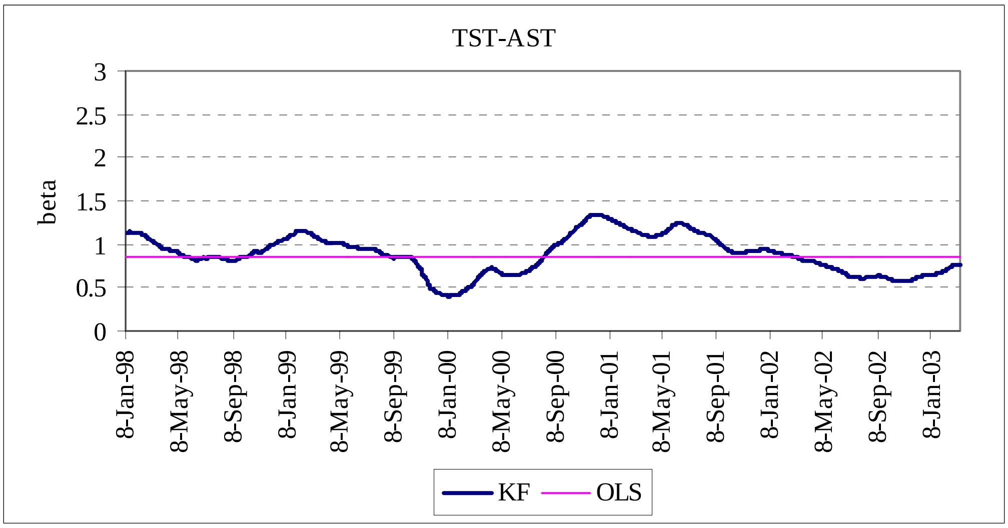
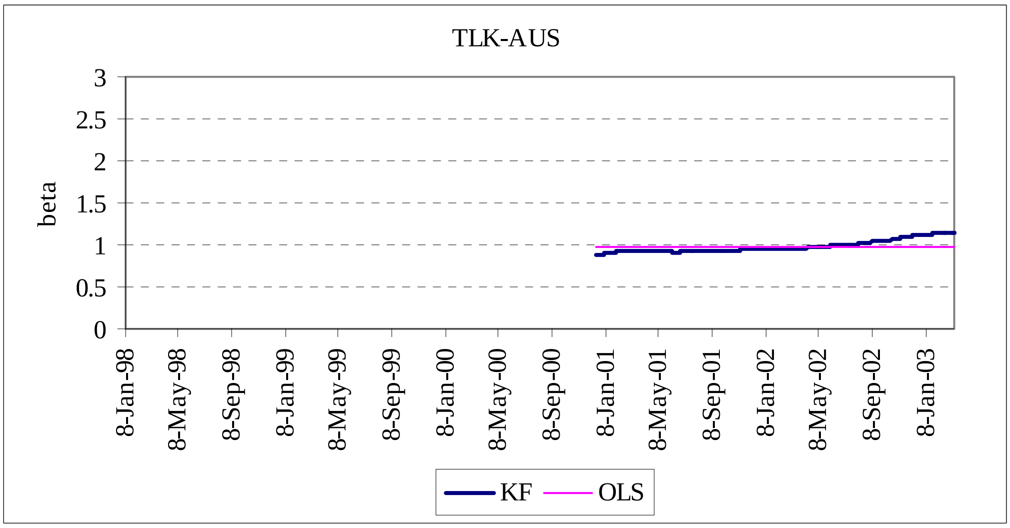
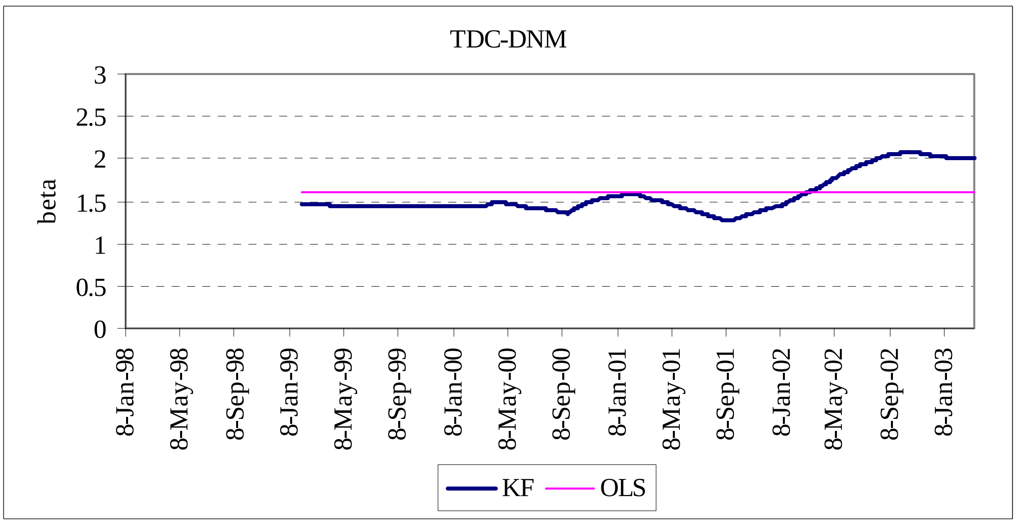
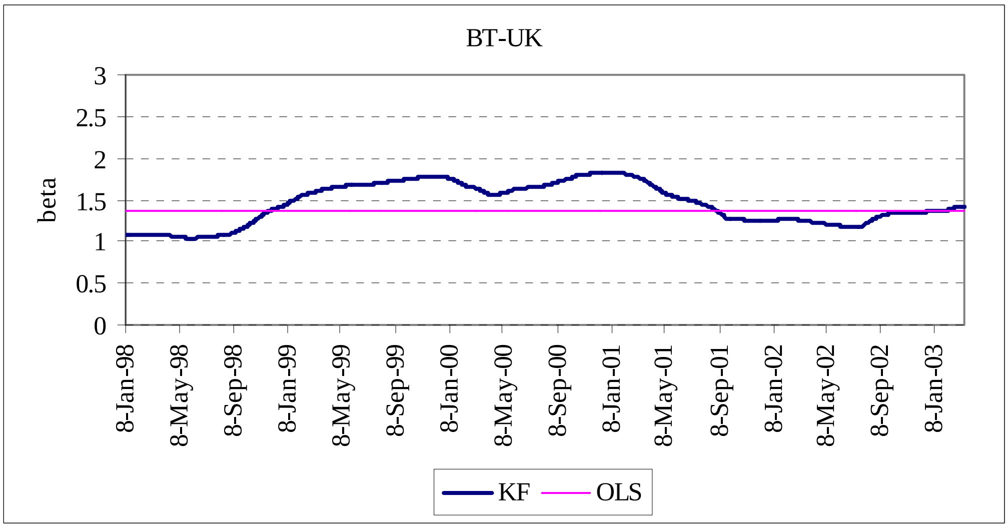
Appendix 1

a) Time-varying (KF) and time-invariant (OLS) betas estimated for the telecom companies listed on developed markets









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beta
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2.5
2
1.5
1
0.5
0
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8-May-98
8-Sep-98
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8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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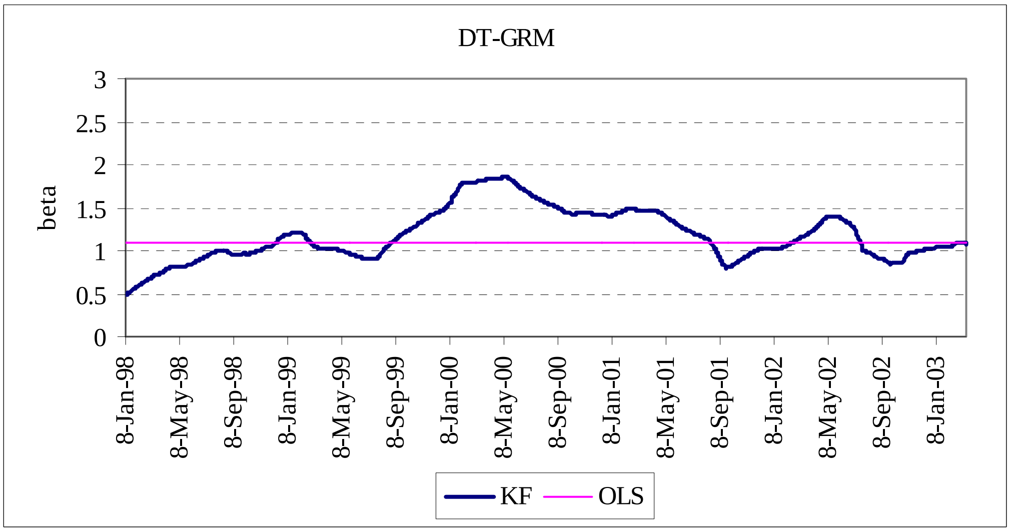
8-Sep-02
8-Jan-03
KF
OLS



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1.5
1
0.5
0
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8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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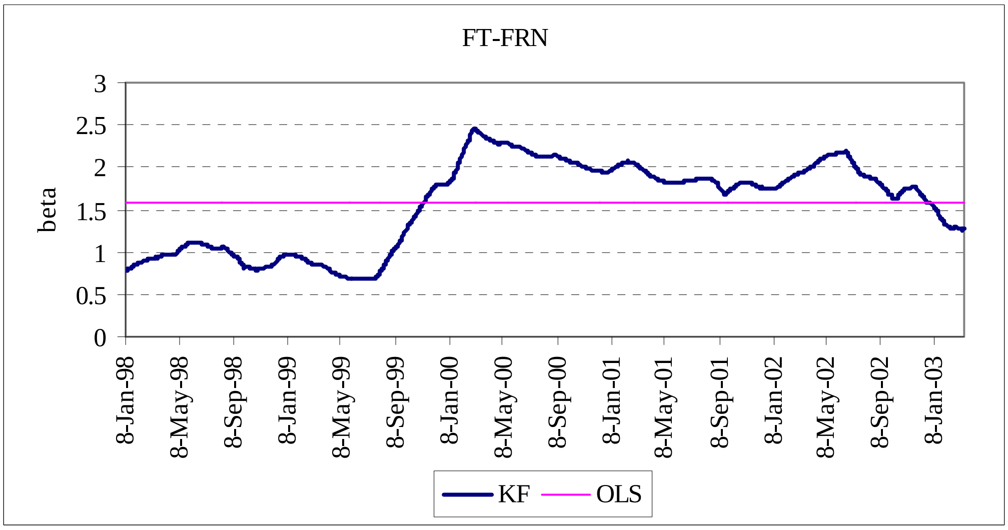
8-Jan-03
KF
OLS



FT-FRN
beta
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2
1.5
1
0.5
0
8-Jan-98
8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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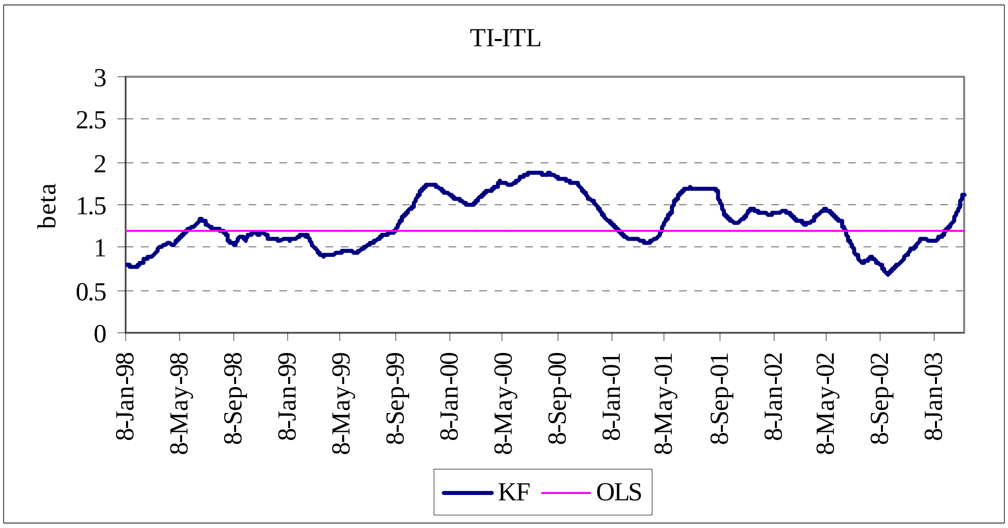
8-Jan-03
KF
OLS



TI-ITL
beta
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1.5
1
0.5
0
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8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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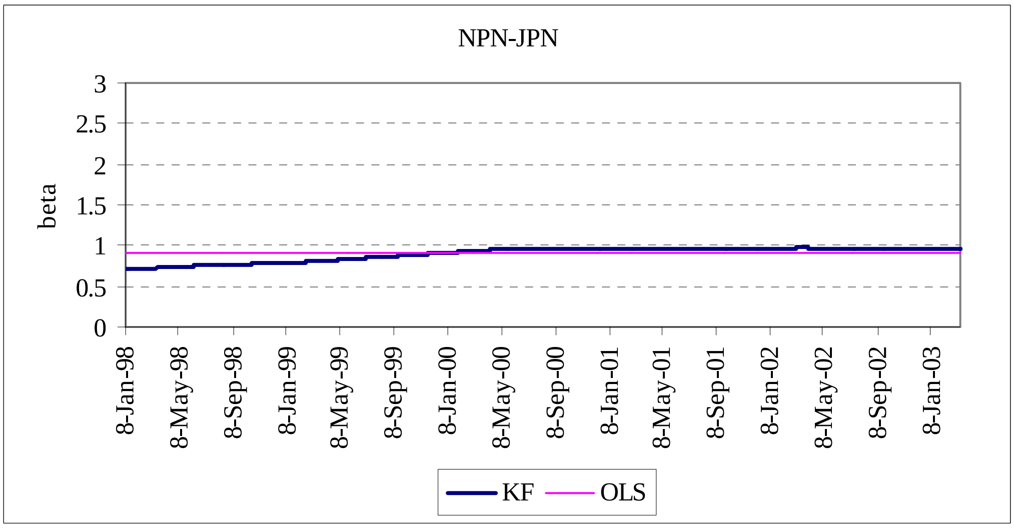
8-Jan-03
KF
OLS



NPN-JPN
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2
1.5
1
0.5
0
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8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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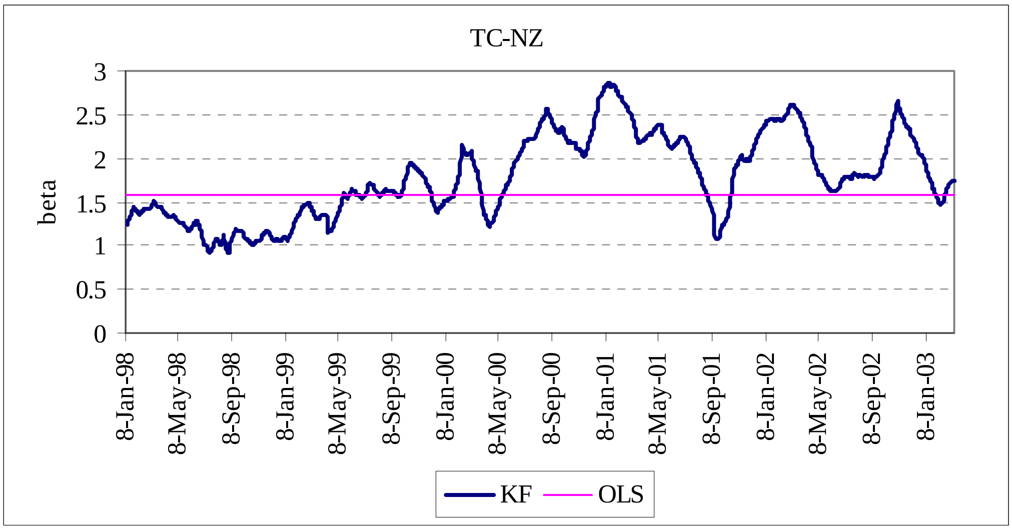
8-Jan-03
KF
OLS



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1.5
1
0.5
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8-Sep-98
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8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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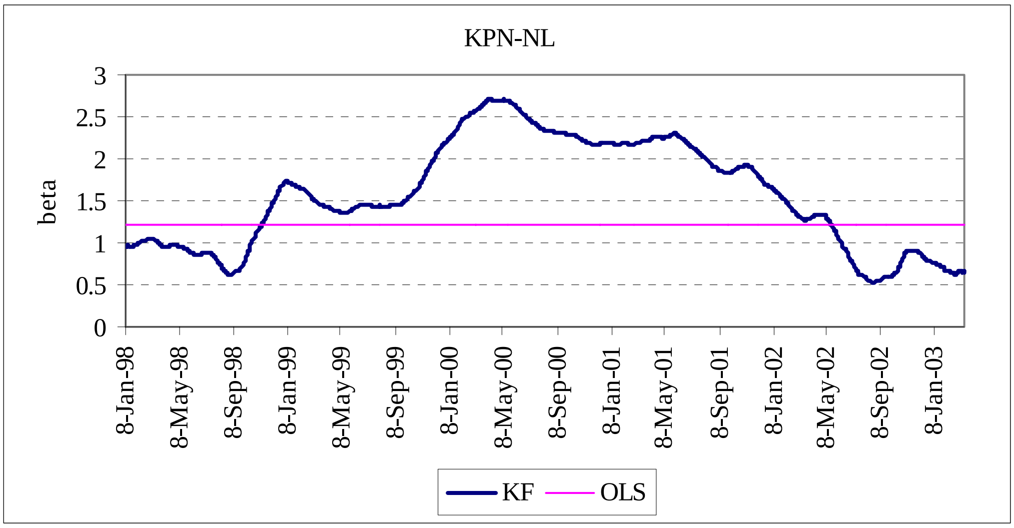
8-Jan-03
KF
OLS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1.5
1
0.5
0
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8-May-98
8-Sep-98
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8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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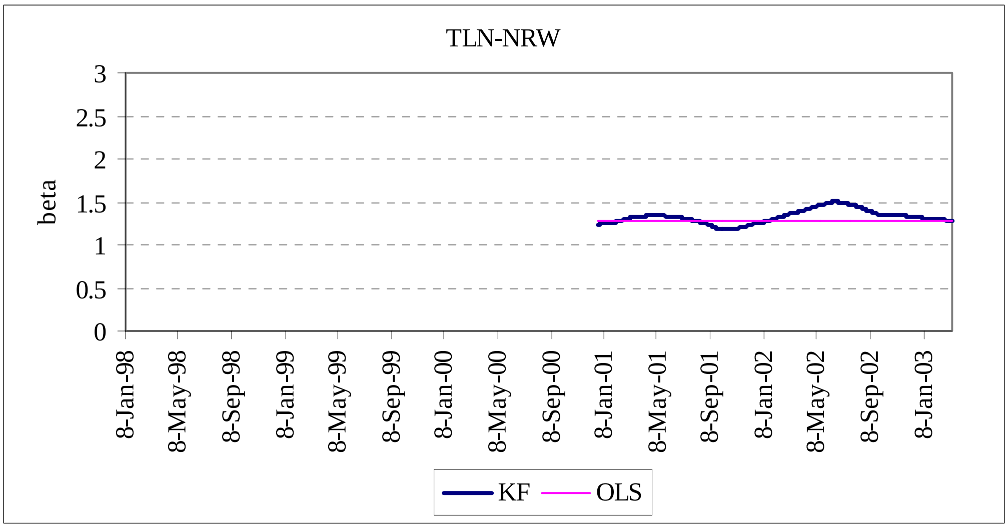
8-Jan-03
KF
OLS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beta
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1.5
1
0.5
0
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8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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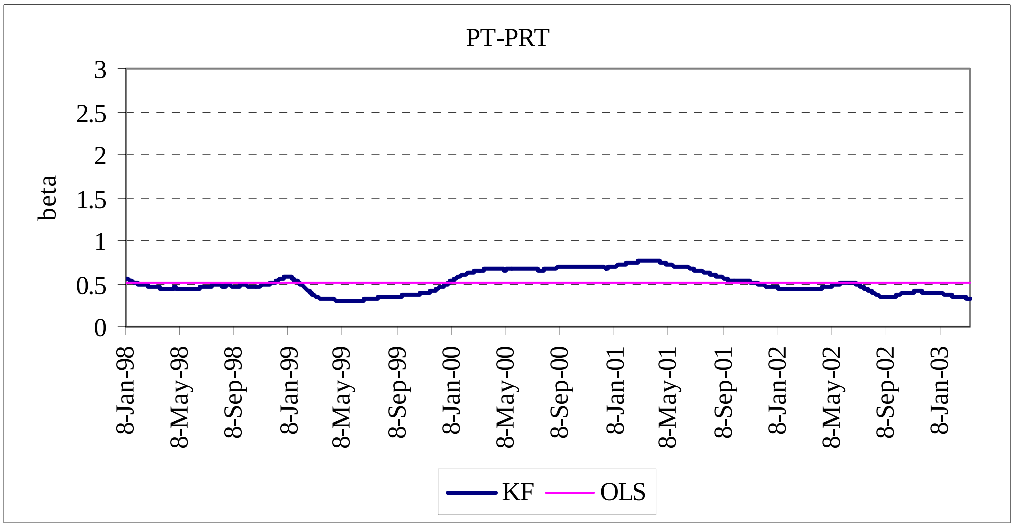
8-Jan-03
KF
OLS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beta
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2.5
2
1.5
1
0.5
0
8-Jan-98
8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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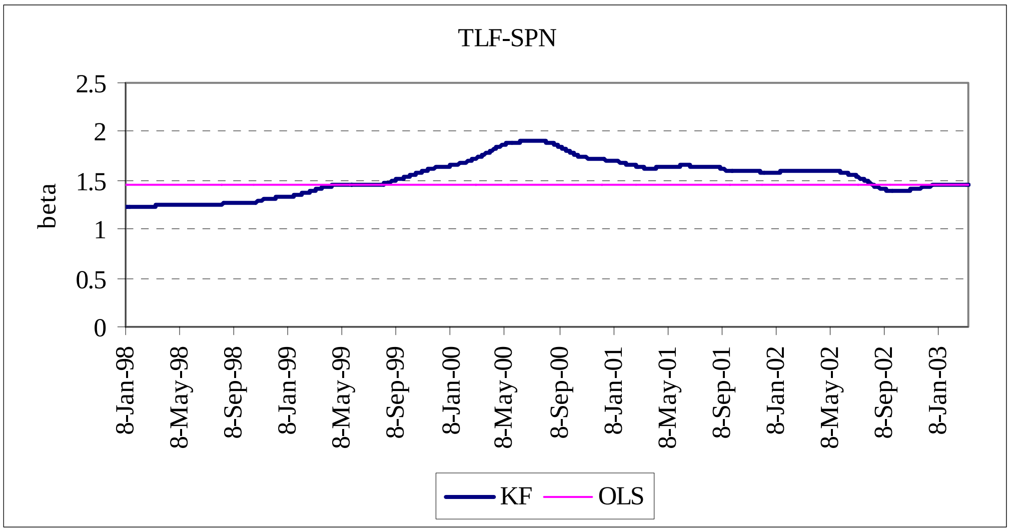
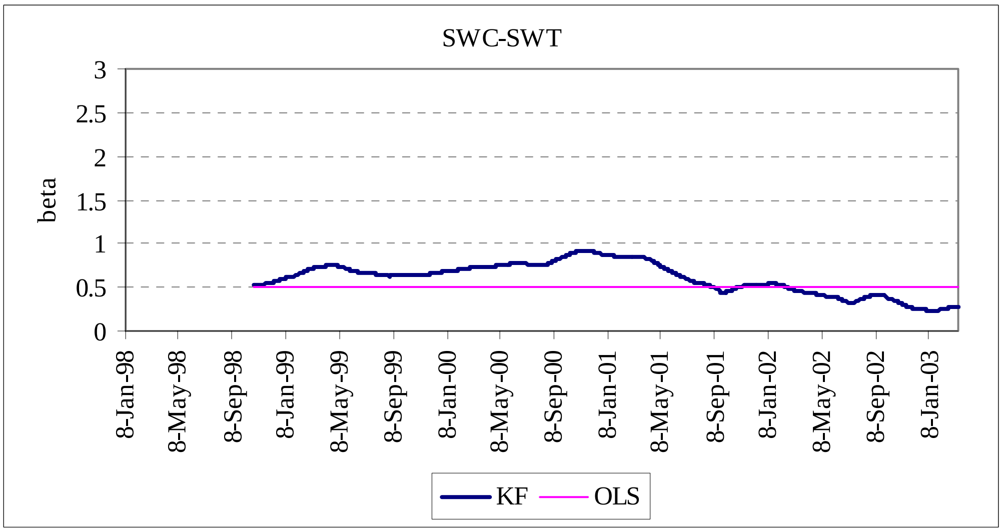
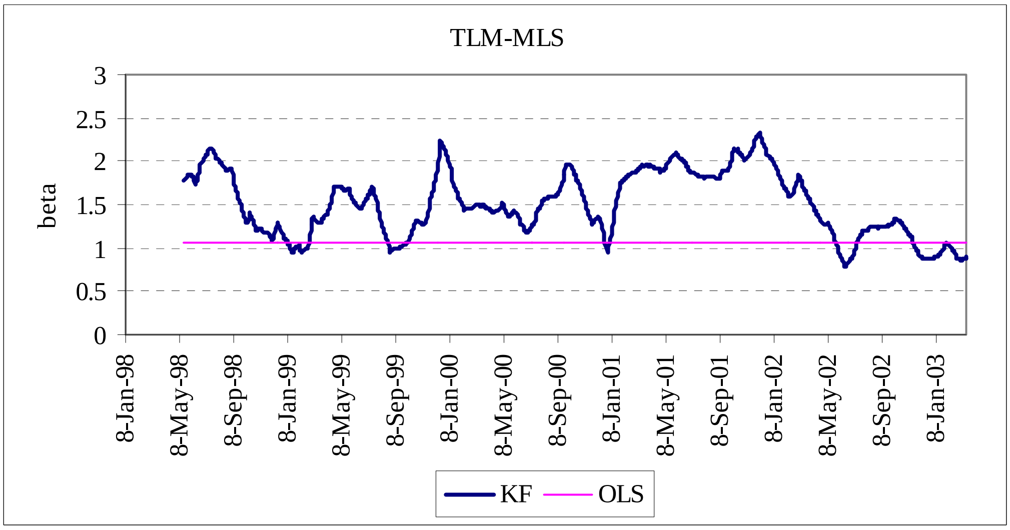
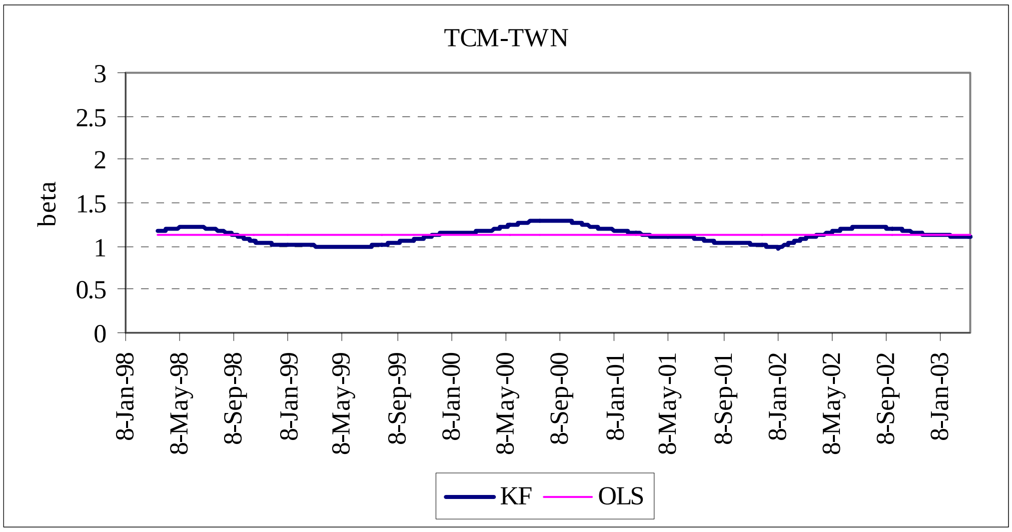
8-Jan-03
KF
OLS





b) Time-varying (KF) and time-invariant (OLS) betas estimated for the telecom companies listed on emerging markets




TCM-TWN
beta
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2.5
2
1.5
1
0.5
0
8-Jan-98
8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
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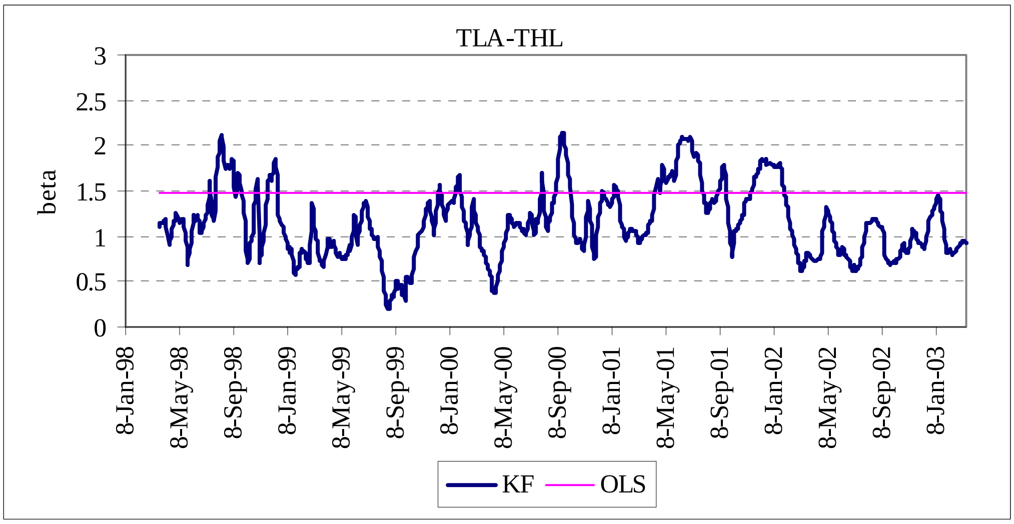
8-Jan-03
KF
OLS


TLA-THL
beta
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2.5
2
1.5
1
0.5
0
8-Jan-98
8-May-98
8-Sep-98
8-Jan-99
8-May-99
8-Sep-99
8-Jan-00
8-May-00
8-Sep-00
8-Jan-01
8-May-01
8-Sep-01
8-Jan-02
8-May-02
8-Sep-02
8-Jan-03
KF
OLS

Appendix 2

GARCH effects. Standard errors in parenthesis.

Company code	Coefficients		
	θ_0	θ_1	θ_2
TLK-AUS	0.000	0.139	0.001
	(0.000)	(0.011)	(0.000)
TDC-DNM	0.000	0.857	0.065
	(0.000)	(0.037)	(0.003)
BT-UK	0.000	0.908	0.030
	(0.000)	(0.046)	(0.004)
FT-FRN	0.000	0.877	0.075
	(0.000)	(0.041)	(0.006)
DT-GRM	0.000	0.739	0.000
	(0.000)	(0.003)	(0.001)
TI-ITL	0.000	0.845	0.102
	(0.000)	(0.005)	(0.000)
TC-NZ	0.000	0.785	0.066
	(0.000)	(0.030)	(0.003)
KPN-NL	0.000	0.900	0.083
	(0.000)	(0.036)	(0.004)
TNR-NRW	0.000	0.005	0.000
	(0.003)	(0.355)	(0.001)
PT-PRT	0.000	0.968	0.017
	(0.000)	(0.000)	(0.000)
TLF-SPN	0.000	0.789	0.092
	(0.000)	(0.011)	(0.001)
SWC-SWT	0.000	0.921	0.060
	(0.000)	(0.039)	(0.003)
TST-AST	0.000	0.273	0.588
	(0.000)	(0.059)	(0.071)
NPN-JPN	0.000	0.965	0.000
	(0.000)	(0.038)	(0.000)
TLM-MLS	0.000	0.688	0.093
	(0.000)	(0.036)	(0.005)
TCM-TWN	0.000	0.846	0.053
	(0.000)	(0.053)	(0.009)
TLA-THL	0.000	0.806	0.083
	(0.000)	(0.036)	(0.004)

Appendix 3

Estimated parameters and adjusted R-squared statistics for OLS regressions with Newey-West corrections. Standard errors in parenthesis.

Company code	Adjusted R-squared	Coefficients	
		α	β
TLK-AUS	0.177	0.0002	0.979
		(0.0008)	(0.088)
TDC-DNM	0.167	-0.001	1.603
		(0.0007)	(0.109)
BT-UK	0..327	-0.0002	1.378
		(0.0007)	(0.054)
FT-FRN	0.432	-0.0002	1.564
		(0.0008)	(0.049)
DT-GRM	0.385	0.0000	1.098
		(0.0007)	(0.038)
TI-ITL	0.592	0.0000	1.196
		(0.0004)	(0.027)
TC-NZ	0.641	-0.0003	1.574
		(0.0002)	(0.032)
KPN-NL	0.274	0.0000	1.191
		(0.0009)	(0.053)
TNR-NRW	0.436	0.0002	1.290
		(0.0008)	(0.061)
PT-PRT	0.083	0.0000	0.501
		(0.0008)	(0.045)
TLF-SPN	0.713	0.0001	1.464
		(0.0004)	(0.025)
SWC-SWT	0.125	0.0003	0.482
		(0.0005)	(0.038)
TST-AST	0.157	0.0001	0.859
		(0.0004)	(0.054)
NPN-JPN	0.309	-0.0003	0.906
		(0.0005)	(0.037)
TLM-MLS	0.562	-0.0003	1.056
		(0.0004)	(0.024)
TCM-TWN	0.374	-0.0001	1.123
		(0.0007)	(0.037)
TLA-THL	0.477	-0.0009	1.469
		(0.0008)	(0.039)

Appendix 4: Gearing ratios

a) Developed sample

	NPN-JPN	TST-AST	TC-NZ	BT-UK	TDC-DNM	TI-ITL	DT-GRM	FT-FRN	PT-PRT	KPN-NL	TLF-SPN	TNR-NRW	TLK-AUS	SWC-SWT
3/31/97	25.35%		12.53%	0.62%										
6/30/97														
12/31/97						20.62%	44.69%	31.63%	10.49%	10.06%	34.38%			
3/31/98	21.75%		9.43%	8.71%										
6/30/98		11.17%												
12/31/98					8.45%	18.07%	30.34%	15.85%	32.92%	15.75%	32.17%			9.11%
3/31/99	18.91%		8.88%	1.44%										
6/30/99		5.16%												
12/31/99					10.28%	9.83%	15.56%	9.81%	19.70%	3.79%	19.88%			12.04%
3/31/00	14.35%			10.22%										
6/30/00		9.14%	21.72%											
12/31/00					16.65%	20.84%	36.58%	36.51%	27.27%	65.26%	25.27%			12.05%
3/31/01	29.09%			45.42%										
6/30/01		15.23%	33.52%											
12/31/01					35.18%	28.49%	43.80%	55.04%	33.21%	55.15%	28.88%	15.30%	71.24%	-4.98%
3/31/02	39.20%			36.07%										
6/30/02		16.94%	36.75%											
12/31/02					40.32%		54.21%	77.38%		44.41%	35.47%	32.96%	47.89%	6.18%

b) Emerging sample

	TLM-MLS	TCM-TWN	TLA-THL
3/31/97			
6/30/97			
12/31/97			
3/31/98			
6/30/98			
12/31/98	16.05%	7.97%	58.99%
3/31/99			
6/30/99			
12/31/99	22.22%	11.38%	51.04%
3/31/00			
6/30/00			
12/31/00	11.28%	9.02%	53.11%
3/31/01			
6/30/01			
12/31/01	10.71%	16.73%	57.75%
3/31/02			
6/30/02			
12/31/02	16.02%	18.65%	69.78%