RISK AND RETURN IN THE SPANISH STOCK MARKET

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Prepared for the VII Simposium of *Moneda y Crédito*
October 1994
Revised: February 1995

* I am grateful to the discussants (Begoña Basarrate and Amado Peiró), and the editorial board of Moneda y Crédito for their suggestions. I should also thank Gonzalo Rubio for allowing me to use his database (GRSP). Of course, the usual caveat applies.

Abstract

In this paper we use Spanish data to test the restrictions that a dynamic APT-type asset pricing model imposes on the risk-return relationship. For monthly returns on ten size-ranked portfolios and a value-weighted index, we find that those restrictions are rejected for different versions of the model over the period 1963-1992, as well as over two subsamples. The evidence for the conditional models suggests that the Spanish stock market is segmented, which probably reflects the fact that it is only deep for a few stocks.

1. Introduction

Empirical tests of asset pricing theories have traditionally focused on their cross-sectional implications by checking if the models could explain differences in asset returns, at least in terms of temporal averages. For the Spanish case, for instance, Palacios (1973), Berges (1984), Rubio (1988) and Gallego, Gómez and Marhuenda (1992) test, without much success, whether there is a positive linear relationship between the average return on an asset over time and the unconditional covariance of that asset with the market portfolio, as postulated by the static version of the Capital Asset Pricing Model (CAPM)

Recently, the emphasis has shifted towards intertemporal asset pricing models in which agents actions are based on the distribution of returns conditional on the available information, which is obviously changing. This is partly motivated by the fact that, nowadays, it is well documented and widely recognised that the volatility of financial markets changes over time. Besides, the new approach has had some empirical success. For instance, Ng, Engle and Rothschild (1992) found that, unlike in a static setting, the basic restrictions of a CAPM-type model were not rejected with US data when they allowed the variances and covariances of the assets to vary over time.

At the same time, there has been a renewed interest in studying the temporal variation in the volatility of the Spanish stock market (e.g. Alonso (1994), Peiró (1992), or Peña and Ruiz (1993)). Nevertheless, these studies are mainly descriptive and have only considered the market index, with some exceptions, like Alonso and Restoy (1995), who study the risk-return relationship for the Spanish portfolio of the Morgan-Stanley database.

Therefore, it seems appropriate to combine both strands of the literature, and study the valuation of risk in the Spanish stock market at a disaggregate level by testing dynamic asset pricing models which explicitly allow for time-variation in the variances and covariances of the assets. The purpose of this paper is precisely that. As theoretical model, we shall use the dynamic version of the Arbitrage Pricing Theory (APT) developed in King, Sentana and Wadhwani (1994), which is briefly reviewed in section 2. The econometric methodology is explained in section 3, while a description of the data can be found in section 4. The main empirical results are discussed in section 5. We also look at the seasonality of the Spanish stock market in section 6. Finally, section 7 contains the main conclusions.

2. Theoretical Model

The theoretical asset pricing model used is developed in King, Sentana and Wadhwani (1994), where a more rigorous and detailed discussion can be found. Formally, the model is based in a world with an infinite number of primitive assets. The (gross) return of asset i during period t, R_{it} (i=1,2,...) is generally uncertain since the asset is risky. The exception is a riskless asset, whose return, R_{0t}, is determined at the end of period t-1 when decisions are taken. It is important to emphasise that the analysis is carried out in terms of the conditional distribution of returns, where the relevant information set, I_{t-1}, contains at least the past values of asset returns.

The basic assumption made on the stochastic structure of returns for the primitive assets is that their unanticipated components have a conditional factor representation, so that we can write returns measured in excess of the riskless asset, $r_{it}=R_{it}-R_{0t}$, as:

$$r_{it} = \mu_{it} + \beta_{i1t}f_{1t} + \beta_{i2t}f_{2t} + \ldots + \beta_{ikt}f_{kt} + v_{it} \qquad (i=1,2,\ldots) \qquad (1)$$

where μ_{it}, the conditional expectation of r_{it}, is the risk premium on asset i, f_{jt} (j=1,2,...,k finite) are common factors which capture systematic risk affecting all assets, β_{ijt} (i=1,2,...;j=1,2,...,k) are the associated factor loadings known in t-1 which measure the sensitivity of the asset to the common factors, while v_{it} are idiosyncratic terms which reflect risks specific to asset i. It is important to stress that, in general, the factor loadings change from asset to asset.

To guarantee that common and specific factors are innovations, we assume that they are unpredictable. Nevertheless, their conditional variances, λ_{jt} (j=1,...,k) and ω_{it} (i=1,...), which reflect their volatility, may change over time in a predictable manner. In this way, it is possible to allow for short and long periods of low and high volatility, both for all asset simultaneously, and for each one separately.

By construction, specific risks are (conditionally) orthogonal to the common factors. We also assume (without loss of generality at the theoretical level) that the common factors represent orthogonal influences. Furthermore, for simplicity we assume that the idiosyncratic terms are conditionally uncorrelated to each other.

Under mild no arbitrage conditions, and other assumptions about diversification, it is possible to prove that the risk premium on asset i will be a linear combination of the volatility associated with the common factors, with weights proportional to the corresponding factor loadings. Specifically,

$$\mu_{it} = \beta_{i1t}\lambda_{1t}\tau_{1t} + \beta_{i2t}\lambda_{2t}\tau_{2t} + \dots + \beta_{ikt}\lambda_{kt}\tau_{kt} \qquad (2)$$

An important feature of (2) is that it provides a connection between conditional means of returns, or risk premia, and their conditional variances and covariances, which measure their volatility and covariation. As we shall see below, such a relationship is very convenient for estimation purposes.

Equation (2) above can also be interpreted as saying that the risk premium on an asset is a linear combination of its factor loadings or betas, with weights common to all assets. As usual, the common weights, $\pi_{jt}=\lambda_{jt}\tau_{jt}$, can be understood as the risk premium on the j-th (limiting) factor mimicking portfolio (i.e. a well-diversified portfolio with unit loading on factor j and zero loadings on the others). Therefore, we can also say that asset risk premia are linear combinations of k risk premia associated with the common factors. In that sense, expression (2) above could also be obtained with a conditional version of the exact APT. Given that λ_{jt} is the volatility of both factor j and its representing portfolio, and π_{jt} the risk premium on that portfolio, we can interpret $\tau_{jt}=\pi_{jt}/\lambda_{jt}$ as the "price of risk" for that factor. That is, the amount of expected return that agents would be willing to give away to reduce its variability by one unit.

It is important to emphasise that, according to the model, risk prices depend on the factors, not on the assets, since otherwise there would be arbitrage opportunities. Furthermore, the model also implies that specific risk, as measured by the volatility of the idiosyncratic terms, should not be priced because it can be diversified away. Its price, thus, should be zero. These fundamental restrictions shall be tested.

The model to be estimated is then

$$r_{it} = \beta_{i1t}\lambda_{1t}\tau_{1t} + \ldots + \beta_{ikt}\lambda_{kt}\tau_{kt} + \beta_{i1t}f_{1t} + \ldots + \beta_{ikt}f_{kt} + v_{it} =$$

$$= \beta_{i1t}(\lambda_{1t}\tau_{1t}+f_{1t}) + \ldots + \beta_{ikt}(\lambda_{kt}\tau_{kt}+f_{kt}) + v_{it} \qquad (3)$$

For the case of a single factor whose representing portfolio is actually the market portfolio, the model above coincides with a conditional version of the CAPM in which risk premia are proportional to the conditional covariance of each asset with the market[1].

One problem with the above expression is that it does not necessarily price derivative assets correctly. Nevertheless, it can be safely applied to portfolios of the primitive assets. Consider for simplicity the case of a single common factor. Let r_{pt} be the excess return on an portfolio with

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[1] In fact, our model is also compatible with the CAPM under more general circumstances. In particular, if the market portfolio is well-diversified and the prices of risk are proportional to the influence of the factors on the market portfolio, equation (2) above also coincides with a conditional version of the CAPM.

weights w_{pt} (known in period t-1). Our assumptions imply that we can write r_{pt} as:

$$r_{pt} = \beta_{p1t}\lambda_{1t}\tau_{1t}+\beta_{p1t}f_{1t}+v_{pt} = \beta_{p1t}(\lambda_{1t}\tau_{1t}+f_{1t})+v_{pt} \tag{4}$$

where the factor loading coefficient, β_{p1t}, and the specific risk component, v_{pt}, are a linear combination of the individual β_{i1t}'s and v_{it}'s, but the common factor, its variance and price of risk are the same as in equation (3). Note that if the portfolio were well-diversified (i.e. v_{pt}=0), r_{pt} could be used as factor representing portfolio.

From an economic point of view, the hypothesis of interest are the following:

- Are the risk prices different from zero?
- Is the Spanish stock market integrated, in the sense that the same risks are valued in the same way across assets?
- Is idiosyncratic risk priced?
- Are there systematic biases in risk premia which cannot be explained by the model, such as "size effects" or "January effects"?

But before, we have to transform equation (3) above (which holds period by period) into an estimable model of the time-variation in risk premia. To do so, we assume for simplicity that, for a given unconditional normalization of the factors, the factor loadings and the prices of risk are time-invariant. Such an assumption is observationally equivalent to a model in which the conditional variance of the factors is constant, but the betas of different assets on a factor change proportionately over time. Importantly, if the unconditional variances of the factors and idiosyncratic disturbances are bounded, our assumption of constant betas implies that the unconditional covariance matrix of the <u>innovations</u> in returns has an exact factor structure, making our model compatible with traditional factor analysis. Besides, if we call μ_i=E(μ_{it})=E(r_{it}) the (temporal) average risk premium, such an assumption also implies that

$$\mu_i = \beta_{i1}\lambda_1\tau_1+...+\beta_{ik}\lambda_k\tau_k \tag{5}$$

where $\lambda_j=E(\lambda_{jt})=V(f_{jt})$ is the unconditional variance of factor j.

Finally, we need to specify the temporal variation in the volatility of common and idiosyncratic factors to complete the model. In practice, we shall assume that such variances can be modelled as univariate GARCH-type processes. In particular, we assume that they follow the GQARCH(1,1) (quadratic GARCH) model in Sentana (1994). This model not only captures the autocorrelation in stock market volatility, but also allows for asymmetric effects in the response of volatility to positive and negative shocks of the same size, and has been successfully applied to US data (see Campbell and Hentschel (1992)) and UK data (see e.g. Demos, Sentana and Shah (1993)).

3. Econometric methodology

Under the assumption of conditional normality, the model can be estimated for N assets simultaneously by maximum likelihood. But first, it is convenient to obtain initial values by means of the EM algorithm in Demos and Sentana (1992). This algorithm uses the Kalman filter, and yields the best estimates of the common factors in the mean square error sense. Given that the econometrician's information set is smaller than the agents, we have adopted the correction to the conditional variances in Harvey, Ruiz and Sentana (1992).

However, estimation can be considerably simplified if we have data on factor representing portfolios. The intuition can be more easily obtained for the case of single common factor. Given that the unconditional scaling of the factors is free, we can set $\beta_{p1}=1$ in equation (4) without loss of generality. If we add such a portfolio to the N assets at hand, and estimate by maximum likelihood, it is easy to prove, under our assumptions, that efficient estimates of the price of risk and the conditional variance parameters corresponding to the common factor can be obtained from a univariate GQARCH-M model for the representing portfolio, while efficient estimates of the factor loadings and the conditional variance parameters of the idiosyncratic terms are obtained from univariate GQARCH regressions of each asset return on the return of the basis portfolio[2]. In our empirical application, we shall use both estimation procedures.

4. Data

The database used contains arithmetic monthly returns (adjusted for dividends and capital changes) on 164 firms listed in the Spanish stock market between January 1963 and December 1992. In particular, we work with 360 monthly observations for ten equally-weighted size-ranked portfolios, and with an eleventh portfolio, hereinafter VW, which is a weighted average of all assets, with weights that depend on market capitalization at the end of the previous year. Studies for other markets suggest that, a priori, such an aggregation should show more cross-sectional variation in the factor loadings than a sectorial-based aggregation. It is important to mention that all the assets available in each period were used to form portfolios. In this way, we avoid survivor-type biases that could arise if we only used data on those shares that have been listed for the complete sample period. As a safe asset, we used T-bill returns on the secondary market after 1982, and the average lending rate from banks and saving institutions before (see Rubio (1988) for details).

Figure 1 shows the returns on the VW index in excess of the safe asset. Apart from noticeable events, like the October 1987 crash, there are periods of high volatility followed by more quiet ones, which confirms the importance of modelling its time-variation, and suggests that there may be substantial differences between the traditional static approach and the conditional one that we propose. In fact, the changing nature of

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[2] Ordinary least squares regressions would yield consistent estimators, which nevertheless are generally inefficient unless the conditional idiosyncratic variance is constant. Note that the assumption of an exact factor structure implies that there is no efficiency gain in using system estimation techniques.

volatility would be even more noticeable if we considered weakly and daily returns. In this respect, it would certainly be desirable to use data at a higher frequency. Unfortunately, such data is only available for some aggregate indices, generally without adjustments for dividend payments or stock splits. Besides, since the Spanish stock market is relatively thin, with most trades concentrated in a few stocks, daily or weakly data could suffer from non-synchronous trading.

5. Empirical results

5.1 The unconditional evidence

As a benchmark, we present the results obtained ignoring the dynamics in first and second moments. The average excess return and standard deviation for the eleven portfolios are included in table 1. As can be observed, returns on small firms generally have larger mean and variances than returns on big firms.

Assuming that the VW portfolio is diversified, and imposing the restrictions derived from the asset pricing model in section 2, the maximum likelihood estimators of the betas in a single factor model for the ten size-ranked portfolios can be obtained from the least squares regression of each portfolio return on the market return. OLS estimators are efficient under the assumption that the conditional variances of the idiosyncratic terms are constant. In this sense, the model is exactly identical with a traditional CAPM. The parameter estimates are presented in table 2. In such a static setting, the cross-sectional restrictions amount to the ratio risk premium/beta being the same for all assets, and equal to the risk premium on the market as a whole.

A simple, yet powerful way of testing such restrictions consists in including a constant in each of the ten regressions, and checking if a significant coefficient is obtained (cf. Gibbons, Ross and Shanken (1989)). The regression intercepts, which measure "abnormal" returns from the point of view of the model, are known as Jensen's alphas in the portfolio evaluation literature. The estimated coefficients can be found in table 3. The null hypothesis is rejected individually in several instances at conventional levels, especially for firms with small capitalizations, which suggests a certain "size effect". Besides, the joint Wald test takes the value 45.195 (p-value<0.001%), so the null hypothesis that all intercepts are zero is also rejected[3]. Hence, the results confirm the existence of systematic biases in risk premia for the Spanish stock market, at least when a value weighted index is used as benchmark portfolio (see Rubio (1988)).

The results for the individual tests are graphically represented in figure 2, where we have plotted the average excess return for the ten size portfolios (cf. table 1), and their market betas (cf. table 2). In figure 2, Jensen's alphas correspond to the vertical distances between the points that represent each portfolio, and the risk premia implied by the model, which lie on the security market line. As one would expect from the statistical results, some differences are clearly substantial.

The joint test can also be represented graphically. As the mathematics of mean-variance portfolio analysis implies that there is a linear relationship between risk premia and betas with respect to any efficient portfolio other than the safe asset (see Huang and Litzenberger (1988)), at the end of the day, the only restriction that the CAPM actually imposes is that the market portfolio is mean-variance efficient. Figure 3 shows the position in mean-standard deviation space of the ten size-ranked portfolios, the efficient frontier and the tangency portfolio. If the restrictions of the model were satisfied, the VW portfolio should coincide with the tangency portfolio. However, it is clear that this is not the case. In this framework, the joint Wald test above examines if the ratio mean-standard deviation for the VW portfolio coincides with the same ratio for the tangency portfolio (see Gibbons, Ross and Shanken (1989)). In the portfolio evaluation jargon, the joint test checks if the Sharpe ratio for the VW portfolio is smaller than the maximum average return

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[3] Sánchez Torres (1994) reaches the same conclusion with a modified Wald test robust to autocorrelation and heteroskedasticity.

attainable per unit of risk.

The above tests have also been computed for two subsamples: 1963:01-1978:12 and 1979:01-1992:12. The motivation for the chosen sample split is twofold: the institutional changes in the Spanish stock market during 1977 and 1978, and the changes in capital gains taxation resulting from the 1979 fiscal reform (see also section 6 below). For both subsamples the model restrictions are rejected at the 5% level (joint Wald tests of 26.005 and 36.982, with p-values 3.73% and 0.006% respectively).

In principle, though, it is possible that the VW index may not be the best portfolio to proxy for the "market" in the CAPM sense; or in the context of our model, it may not be an appropriate representing portfolio for the common factor. One potential solution would be to use alternative benchmark portfolios, such as an equally-weighted index. However, since the ten size-ranked portfolios are themselves equally-weighted, figure 3 clearly suggests that an equally-weighted market portfolio would be too far away from the efficient frontier for the model restrictions not to be rejected.

Another attractive possibility consists in avoiding the specification of the basis portfolio, and estimating a model with a single common factor for the ten size-ranked portfolios by maximum likelihood. Here we shall follow this second route. Nevertheless, it can be proved that, at the end of the day, this approach is basically equivalent to repeating the analysis above using the Kalman filter estimate of the common factor as the benchmark portfolio (see Quah and Sargent (1993))[4].

In this sense, it is important to mention that although its composition is in principle different, the return of the estimated basis portfolio is rather similar to the VW portfolio, with a correlation

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[4] Such a portfolio can also be understood as the one that best explains the covariances between the asset returns (see Sentana and Shah (1994)).

coefficient of 0.9[5]. A convenient way of interpreting the common factor can be obtained by regressing the estimated factor on the set of stock returns. Since we are assuming that the variances and covariances of the asset returns are constant over time, so will be the weights used by the Kalman filter to estimate the factor, and hence, the regression R^2 is 1. However, if we compute an analogous regression for the VW index, the R^2 will not be exactly 1, as the VW index is not equally weighted, although the approximation is rather good (R^2=0.975). The average weights obtained in this way can be found in table 4. As expected, the VW portfolio mainly represents those firms with larger capitalisations. By contrast, the weightings for the estimated factor are more evenly distributed, although they are far from corresponding to those of an equally-weighted index.

The results are presented in table 5 for the normalization $\beta_{10}=1$. Note that the price of common risk is positive and significantly different from zero. However, if we include nine constants in the equations for the smallest rank-sized portfolios, the results in table 6 show that the intercepts are jointly significant (LR=33.196, $\chi^2_{9,0.05}=16.919$), but not individually. The latter result, though, could be partly attributed to the normalization used (i.e. $\alpha_{10}=0$).

The results for the two subsamples are broadly similar, although the price of risk for the common factor is not significantly different from zero in the first period. When we add 9 constants to the risk premia, we reject the null hypothesis at the 5% in both subsamples (LR tests of 27.112 and 19.678 respectively). Thus, it would seem that the change in the factor representing portfolio does not improve much the limited empirical success of the static model.

It is possible that the single factor structure may be too restrictive. Unfortunately, not much can be said with only ten assets, and the choice of the number of factors and their specification ends up being to a large extent arbitrary. An interesting possibility would be to

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[5] The estimation of the factor is rather accurate in the sense that its estimated mean square error is 3%

combine unobservable factors with observable macroeconomic factors, because it would help in the interpretation of the results. However, previous studies at an international level suggest that the macroeconomic factors typically used, often explain only a small proportion of the variance of asset returns (see King, Sentana and Wadhwani (1994)). As a compromise solution, we have estimated a model with two common factors for the eleven portfolios, one observable and one unobservable. The latter does not affect the returns on the VW portfolio, which we still assume diversified, but it affects the risk premia on the ten size-ranked portfolios through the cross-sectional restriction in equation (2)[6]. The estimated model is as follows:

$$r_{it} = \tau_1\lambda_1\beta_{i1}+\tau_2\lambda_2\beta_{i2}+\beta_{i1}f_{1t}+\beta_{i2}f_{2t}+v_{it}\,(i=1,\ldots,10;\beta_{10,2}=1) \qquad (6a)$$

$$r_{vwt}= \tau_1\lambda_1 + f_{1t} \qquad (6b)$$

It is worth mentioning that the estimate of the second factor, which is orthogonal to the VW portfolio by construction, has significant positive weightings on the smaller size-ranked portfolios, and a negative weighting on the tenth portfolio. The results obtained, though, show that when we add 9 constants to equations (6a), the α coefficients are still jointly significant (LR=40.712, $\chi^2_{9,0.05}$=16.919), and the same happens in the two subsamples. Therefore, a static model with both an observable and an unobservable factor does not adequately explain risk premia in the Spanish stock market.

5.2. The conditional evidence

Obviously, we can increase the number of unobservable factors until we explain risk premia satisfactorily. In fact, ten factors suffice! But

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[6] Otherwise, we would be simply allowing for a covariance structure of returns richer than the one considered in the CAPM model above, but the betas and alphas in tables 3 and 4, as well as their standard errors would be numerically identical.

another possibility more closely related to the motivation of this paper is to examine whether the ignored time-variation in risk premia and the conditional covariance matrix of returns may help reconcile the empirical evidence with the model, as Ng, Engle and Rothschild (1992) found for US data. At the same time, the emphasis on conditional moments would allow us to test whether the model restrictions are satisfied not only on average, but also over time. For instance, apart from checking if Jensen's alphas are 0, we can also test hypothesis directly related to the integration or segmentation of the Spanish stock market. In particular, we can test if the prices of the common risks are the same for all assets, and also, if asset risk premia depend on the volatility of their idiosyncratic terms, ω_{it}. Therefore, it is possible in this framework to distinguish empirically between the differential valuation of common risk and the valuation of idiosyncratic risk, which is impossible in an unconditional setting.

As we discussed in section 3, given our maintained assumptions, efficient estimates of the parameters of a conditional factor model with a single observable factor can be obtained from a univariate GQARCH-M model for the VW portfolio, together with 10 univariate GQARCH regressions of the returns of the size-ranked portfolios on the VW index. The parameter estimates obtained in this way can be found in tables 7 and 8, while the estimated conditional standard deviation is represented in figure 4. At a purely descriptive level, it is worth mentioning the very high degree of persistence in volatility, as measured by the sum of the ARCH and GARCH coefficients, and also the asymmetric response of volatility to positive and negative shocks of the same size. However, the asymmetric effect is the opposite to the one found for US and UK returns, in that positive shocks seem to have a larger impact than negative ones in the Spanish stock market.

Turning now to the market price of risk, notice that it is positive but not significantly different from zero. This result is similar to the one obtained by Alonso and Restoy (1995) for the Spanish portfolio in the Morgan-Stanley database with different conditional variance specifications. The estimates in the subsamples are qualitatively similar.

However, the ARCH structure is rather poorly estimated, especially in the second subsample. As we discussed before in section 4, a larger number of observations would be required to capture the temporal variation in volatility at the monthly frequency. For that reason, in the remaining of this section we shall only discuss results for the whole sample.

The estimated betas in table 8 are different from the ones obtained by least squares in table 2, and significantly so in some cases. Such changes are mainly due to the substantial degree of time-variation in the volatility of idiosyncratic components, which imply a substantive difference between the ordinary least squares used in section 5.1 and the "weighted" least squares implicit in the maximum likelihood estimation of the GQARCH regressions. Nevertheless, unlike in the Ng, Engle y Rothschild (1992) paper, the changes in estimated betas are not enough to drive away the joint significance of the alphas in table 9 (LR=37.24, $\chi^2_{11,0.05}$=19.675). Actually, the alphas are larger than in table 3, since the estimate of the market price of risk becomes negative, albeit insignificant, when we add the constants. Furthermore, note that the alpha for the market portfolio is significant too.

Besides, the model is also rejected in other directions more informative from an economic point of view. For instance, when we allow for systematic risk to be valued differently across assets, so that τ may vary with i, we find that the price of risk does not seem to be common (LR=30.78, $\chi^2_{10,0.05}$=18.307). Similarly, if we ask whether unsystematic risk, as measured by the asset-specific conditional variance, ω_{it}, affects risk premia, the result suggest that such risks seem to be rewarded (LR=35.82, $\chi^2_{10,0.05}$=18.307). In view of the assumptions underlying the asset pricing model, our findings can be interpreted as evidence against the integration of the Spanish stock market.

We have also considered a conditional version of the model with an unobservable factor, without substantive changes in the results (cf. section 5.1). The test statistics presented in table 10 confirm that the price of systematic risk, τ, does not seem to be significant; that, in fact, it does not seem to be common; that idiosyncratic risks, ω_{it}, affect risk premia; and that Jensen's alphas are jointly significant, and suggestive of a certain size effect.

Finally, we have also estimated a conditional version of the model with two factors, one observable and one unobservable, with the same basic conclusion: the empirical implications of the asset pricing model in section 2 are again rejected for the Spanish stock market (see table 11).

6. Seasonality in stock returns

So far, we have ignored potential seasonal effects in stock returns. However, the international evidence suggests that returns tend to be higher in January than in other months. Moreover, this anomaly appears to be more pronounced in companies with relatively small market capitalizations. While most of the initial studies only examined US data, subsequent work has found that the January effect is very much an international phenomenon. For instance, Rubio (1988), and Basarrate and Rubio (1990, 1994) have shown that it is also relevant in Spain.

The posited explanations for such a finding go from differential tax treatment of capital gains, to seasonality in the risk-return relationship, and include window-dressing type effects induced by extensive repositioning of professionally managed portfolios at the turn of the year after evaluation. In any case, it is clear that the study of the risk-return relationship in Spain should not be independent of the analysis of the seasonality in returns.

A crude measure of the importance of the January effect during our sample period is given by the 3.897% average monthly excess return for the VW portfolio in January, in contrast to the 0.132% average monthly excess return during the rest of the year (t-ratio =3.708). A similar pattern is also found in the other ten portfolios (joint Wald test=23.862, p-value=0.798%). Nevertheless, seasonality in the risk premium on the market portfolio is compatible with a very simple version of the conditional CAPM in which the market price of risk, τ, is allowed to be different in January from the rest of the year. Such a version could also explain the seasonality in the risk premia of the ten size-ranked portfolios, provided that it were fully induced by the market according to the relationship $\mu_{it}=\beta_i\mu_{vwt}$.

To test this hypothesis, we have added a seasonal dummy variable for January to the regressions of the returns of the ten size-ranked portfolios on the returns of the VW index. The results obtained suggest that seasonal variation in the market price of risk on its own is not enough to explain seasonality in asset risk premia (joint Wald test= 22.339, p-value=1.35%).

An indirect way of examining whether the seasonal behaviour in returns is due to tax considerations consists in controlling for changes in the tax law. In this respect, it is worth mentioning that the taxation of capital gains in Spain was radically changed after the introduction of the income tax reform in 1979, which increased the incentives for end-of-year tax-loss trading. In order to capture the legal change, we have repeated the analysis for the 1963:01-1978:12 and 1979:01-1992:12 subsamples, with rather interesting results. While the average January excess return for the VW portfolio is significantly larger than in the remaining months in both periods, seasonality in the risk premium on the market portfolio is enough to explain seasonality in asset returns in the first period (joint Wald test= 4.665, p-value=91.23%), but not in the second. Therefore, the rejection that we find using data for the whole sample is mainly due to the second subsample (joint Wald test= 29.720, p-value=0.095%). These results are in line with the ones in Basarrate and Rubio (1994), and suggest that risk premia seasonality could be related to tax incentives.

Nevertheless, the seasonality in the mean excess returns for the size-ranked portfolios could also be rationalised within the context of a conditional version of our asset pricing model in which we allow for seasonal variation, not only in the market price of risk, but also in the betas (see Demos, Sentana and Shah (1993)). Indeed, when we regress the size-ranked portfolios returns on the return of the VW index, and the product of the VW return times a January seasonal dummy, the results suggest that the market betas seem to be significantly different in January, particularly for the second subsample. Such a seasonal effect could be due either to seasonal trading for tax reasons, or to the increasing importance of mutual funds during recent years, and the "window-dressing" effect that their annual evaluation may induce.

But from the point of view of testing the asset pricing restrictions, the fundamental question to answer is whether the seasonal variation found in the market price of risk and the betas is enough to explain seasonality in risk premia according to the relationship $\mu_{it}=\beta_{it}\mu_{vwt}$. In this respect, we have tested the significance of including a January dummy in the regressions of the size-ranked portfolio returns on the VW returns, in which betas are allowed to be different in January. The results for the whole sample and the two subsamples indicate that such a seasonal conditional version of the CAPM could explain the "January effect", although in the second subsample they are less conclusive (p-value=6.23%).

However, such a model is not capable of eliminating the systematic pricing biases found in section 5. For instance, even when we allow for seasonal variation in betas, Jensen's alphas are still significantly different from zero for the whole sample and the two subsamples.

7. Conclusions

In this paper we use monthly return data for ten size-ranked portfolios and a capitalisation-weighted index for the Spanish stock market for the period January 1963 - December 1992. We test the restrictions implied by a dynamic APT-type asset pricing model on the risk-return relationship. Our results suggest that such restrictions do not appear to be sustained by the data. The same conclusion is reached in static CAPM-type models with a single observable factor, as well as in models with a single unobservable factor or a combination of the two. The evidence for the 1963:01-1978:12 and 1979:01-1992:12 subsamples is similar in this respect.

Besides, our results do not qualitatively change when we model the time-variation in the covariance matrix of asset returns. In this less restrictive model, we generally find that there are still biases in risk premia, that the price of systematic risk does not appear to be significant when we restrict it to be common, that, in fact, it does not seem to be common, and that idiosyncratic risks matter. Thus, time-variation in conditional moments does not explain the well-documented failure of static asset pricing models for the Spanish case (cf. Ng, Engle and Rothschild (1992) for US data). Moreover, the empirical results for the conditional models clearly point out that the Spanish stock market is probably not integrated.

We have also analysed the seasonality in returns, and in particular, the so-called "January effect". Our results confirm its presence, and suggest that it could be due to tax reasons, or to seasonality in the risk-return relationship. Nevertheless, a version of the CAPM in which we allow the market price of risk and the betas to be different in January from the rest of the year is not able to fully explain systematic biases in risk premia.

Obviously, as is true of virtually all econometric tests of theoretical restrictions, we are testing not only those restrictions, but also all the maintained assumptions that underlie our intertemporal asset pricing model and its empirical implementation. Therefore, as always, rejection could also be due to the failure of some of the maintained assumptions. In this respect, there are some potential extension that may reconcile theory and empirical evidence. An interesting possibility is a version of the model without a safe asset, in which a zero beta portfolio plays a similar role. At the same time, even though the GQARCH model for the conditional variances of common and specific terms can accommodate many of the stylised features of the time variation in volatility, the assumptions of constant factor loadings and prices of risk are, no doubt, potentially restrictive. Therefore, it is conceptually possible that a more flexible parametrisation of the variation over time in the covariance matrix may produce more satisfactory results. Its practical implementation, though, would not be easy. Even with all our restrictions, the conditional model with two factors already involves the joint estimation of 69 parameters.

From an economic point of view, a more illustrative strategy would be to repeat the analysis above, but using returns for individual stocks instead of portfolio returns. Since shares in the Spanish stock market can be broadly divided into two groups, one of larger and well-known firms, with high volume and frequency of trading, and a second group of smaller firms, with low volume and frequency of trading, it may well be that the latter are responsible for the rejection of the different versions of the model. By working with individual stocks, it would be possible to test such a conjecture rigorously, as well as to analyse if the apparent segmentation of the market that we find, is due to tax, sectorial or other reasons. We are currently pursuing this approach.

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TABLE 1

SIZE RANKED PORTFOLIOS AND

VALUE WEIGHTED INDEX

Descriptive Statistics

Sample Period 1963:01-1992:12

DECILE	MEAN	STD. DEV.
1	1.2644	8.7704
2	1.1681	6.6271
3	0.7969	7.3153
4	1.1453	6.9835
5	0.8047	6.5425
6	0.9325	6.1133
7	0.2946	6.4178
8	0.3566	6.4780
9	0.4581	5.8035
10	0.5514	5.4494
VW	0.4454	5.4198

TABLE 2

SIZE RANKED PORTFOLIOS

MARKET β's (Value weighted index)

OLS Regressions $r_{it} = \beta_i r_{vwt} + v_{it}$ (i=1,...,10)

Sample Period 1963:01-1992:12

DECILE	β (s.e.)	s.e. Regression	R^2
1	1.1827 (0.0592)	6.095	0.524
2	0.9047 (0.0446)	4.591	0.533
3	1.0357 (0.0459)	4.736	0.583
4	0.9770 (0.0454)	4.675	0.562
5	1.0297 (0.0338)	3.478	0.720
6	0.9284 (0.0346)	3.571	0.666
7	0.9879 (0.0342)	3.523	0.699
8	0.9993 (0.0344)	3.544	0.701
9	0.9911 (0.0213)	2.200	0.856
10	0.9566 (0.0166)	1.715	0.901

TABLE 3

SIZE RANKED PORTFOLIOS

Jensen's α's (Value weighted index)

OLS Regression $r_{it} = \alpha_i + \beta_i r_{vwt} + v_{it}$ (i=1,...,10)

Sample Period 1963:01-1992:12

DECILE	α (s.e.)
1	0.7427 (0.3204)
2	0.7704 (0.2397)
3	0.3379 (0.2502)
4	0.7149 (0.2447)
5	0.3484 (0.1833)
6	0.5225 (0.1871)
7	-0.1464 (0.1864)
8	-0.0890 (0.1876)
9	0.0168 (0.1165)
10	0.1263 (0.0906)

TABLE 4

AVERAGE WEIGHTS (%)

Based on OLS regression of r_{vwt} and

the factor estimate on r_{it} (i=1,...,10)

Sample Period 1963:01-1992:12

DECILE	VW	Unobservable factor
1	3.629	4.728
2	0.929	8.050
3	-0.382	8.125
4	-1.346	8.163
5	5.323	13.497
6	4.618	10.748
7	3.959	15.001
8	12.718	11.838
9	14.392	12.612
10	56.160	7.238
Total	100	100
R^2	0.9754	1

TABLE 5

SIZE RANKED PORTFOLIOS

Unobservable factor β's

MLE $r_{it} = \tau\lambda\beta_i+\beta_i f_t+v_{it}$ $(i=1,...,10; \beta_{10}=1)$

Sample Period 1963:01-1992:12

DECILE	β (s.e.)	Idiosyncratic Std. Deviation	R^2
1	1.6370 (0.0949)	5.1361	0.6561
2	1.3021 (0.0713)	3.5081	0.719
3	1.4447 (0.0783)	3.6826	0.7458
4	1.3828 (0.0746)	3.5906	0
5	1.3567 (0.0669)	2.7685	0.8204
6	1.2320 (0.0649)	2.9545	0.7658
7	1.3317 (0.0656)	2.6077	0.8344
8	1.3145 (0.0664)	2.9144	0.797
9	1.1736 (0.0580)	2.6668	0.7882
10	1	3.2468	0.644
τ	0.0284 (0.0128)		

TABLE 6

SIZED RANKED PORTFOLIOS

Jensen's α's (Unobservable factor)

MLE $r_{it} = \alpha_i+\tau\lambda\beta_i+\beta_i f_t+v_{it}$ $(i=1,...,10;\ \beta_{10}=1;\ \alpha_{10}=0)$

Sample Period 1963:01-1992:12

DECILE	α (s.e.)
1	0.3671 (0.3930)
2	0.4569 (0.2969)
3	0.0001 (0.3422)
4	0.3886 (0.2910)
5	0.0574 (0.2792)
6	0.2569 (0.2826)
7	-0.4477 (0.2752)
8	-0.3745 (0.2943)
9	-0.1921 (0.2438)
10	0

TABLE 7

VALUE WEIGHTED RETURNS

GQARCH (1,1) - M Parameter Estimates and Standard Errors

Sample Period 1963:01-1992:12

$r_{vwt} = \underset{(0.09687)}{0.00651}\,\lambda_t + f_t$
$\lambda_t = 0.05039 + \underset{(0.03906)}{0.11256}\,f_{t-1} + \underset{(0.02222)}{0.06286}\,f^2_{t-1} + \underset{(0.02342)}{0.93034}\,\lambda_{t-1}$

TABLE 8

SIZE RANKED PORTFOLIOS

MARKET β's (Value weighted index)

FIML $r_{it} = \beta_i r_{vwt} + v_{it}$ (i=1,...,10) $v_{it} | I_{t-1} \sim N(0,\omega_{it})$

Sample Period 1963:01-1992:12

DECILE	β s.e.
1	0.9895 (0.0621)
2	0.8070 0.0000
3	1.0604 (0.0592)
4	0.9619 (0.0468)
5	0.9974 (0.0350)
6	0.9098 (0.0350)
7	0.9362 (0.0390)
8	0.9779 (0.0306)
9	0.9779 (0.0233)
10	1.0139 (0.0142)

TABLE 9

SIZE RANKED PORTFOLIOS AND

VALUE WEIGHTED INDEX

Jensen's α's (Value weighted index)

FIML $r_{it} = \alpha_i + \beta_i r_{vwt} + v_{it}$ (i=1,...,10) $v_{it}|I_{t-1} \sim N(0,\omega_{it})$

$r_{vwt} = \alpha_{vw} + \tau\lambda_t + f_t$ $f_t|I_{t-1} \sim N(0,\lambda_t)$

Sample Period 1963:01-1992:12

DECILE	α (s.e.)
1	1.1924 (0.2884)
2	0.8542 (0.2650)
3	0.9261 (0.3246)
4	0.9689 (0.2865)
5	0.7398 (0.2563)
6	0.9283 (0.2394)
7	0.1201 (0.2400)
8	0.3311 (0.2351)
9	0.6160 (0.2215)
10	0.7059 (0.2126)
VW	.60861 (0.2015)

TABLE 10

SIZE RANKED PORTFOLIOS

(Unobservable Factor)

FIML $r_{it} = \tau\lambda_t\beta_i+\beta_i f_t+v_{it}$ $(i=1,...,10;\ \beta_{10}=1)$

$f_t|I_{t-1}\sim N(0,\lambda_t)$; $v_{it}|I_{t-1}\sim N(0,\omega_{it})$

ASSET PRICING TESTS

1.-	Is systematic risk significantly priced?	LR = 2.270	($\chi^2_{1;0.05}$ = 3.841)
2.-	Is the systematic risk priced differently across assets?	LR = 25.100	($\chi^2_{9;0.05}$ = 16.919)
3.-	Is idiosyncratic risk priced?	LR = 20.846	($\chi^2_{10;0.05}$ = 18.307)
4.-	Does the model price assets correctly on average?	LR = 38.972	($\chi^2_{10;0.05}$ = 18.307)

TABLE 11

SIZE RANKED PORTFOLIOS & VW INDEX

(Observable & Unobservable Factor)

FIML $r_{it} = \tau_1\lambda_{1t}\beta_{i1}+\tau_2\lambda_{2t}\beta_{2t}+\beta_{i1}f_{1t}+\beta_{i2}f_{2t}+v_{it}$

$r_{vwt} = \tau_1\lambda_{1t}\beta_{i1}+f_{1t}$ (i=1,...,10; $\beta_{10,2}$=1)

$f_{jt}|I_{t-1}\sim N(0,\lambda_{jt})$; $v_{it}|I_{t-1}\sim N(0,\omega_{it})$

ASSET PRICING TESTS

1.-	Is systematic risk significantly priced?	Factor 1	LR = 0.420	($\chi^2_{1;0.05}$ = 3.841)
		Factor 2	LR = 4.146	($\chi^2_{1;0.05}$ = 3.841)
2.-	Is systematic risk priced differently across assets?	Factor 1	LR = 24.986	($\chi^2_{10;0.05}$ = 18.307)
		Factor 2	LR = 26.012	($\chi^2_{9;0.05}$ = 16.919)
3.-	Is idiosyncratic risk priced?		LR = 27.376	($\chi^2_{10;0.05}$ = 18.307)
4.-	Does the model price assets correctly on average?		LR = 53.476	($\chi^2_{11;0.05}$ = 19.675)

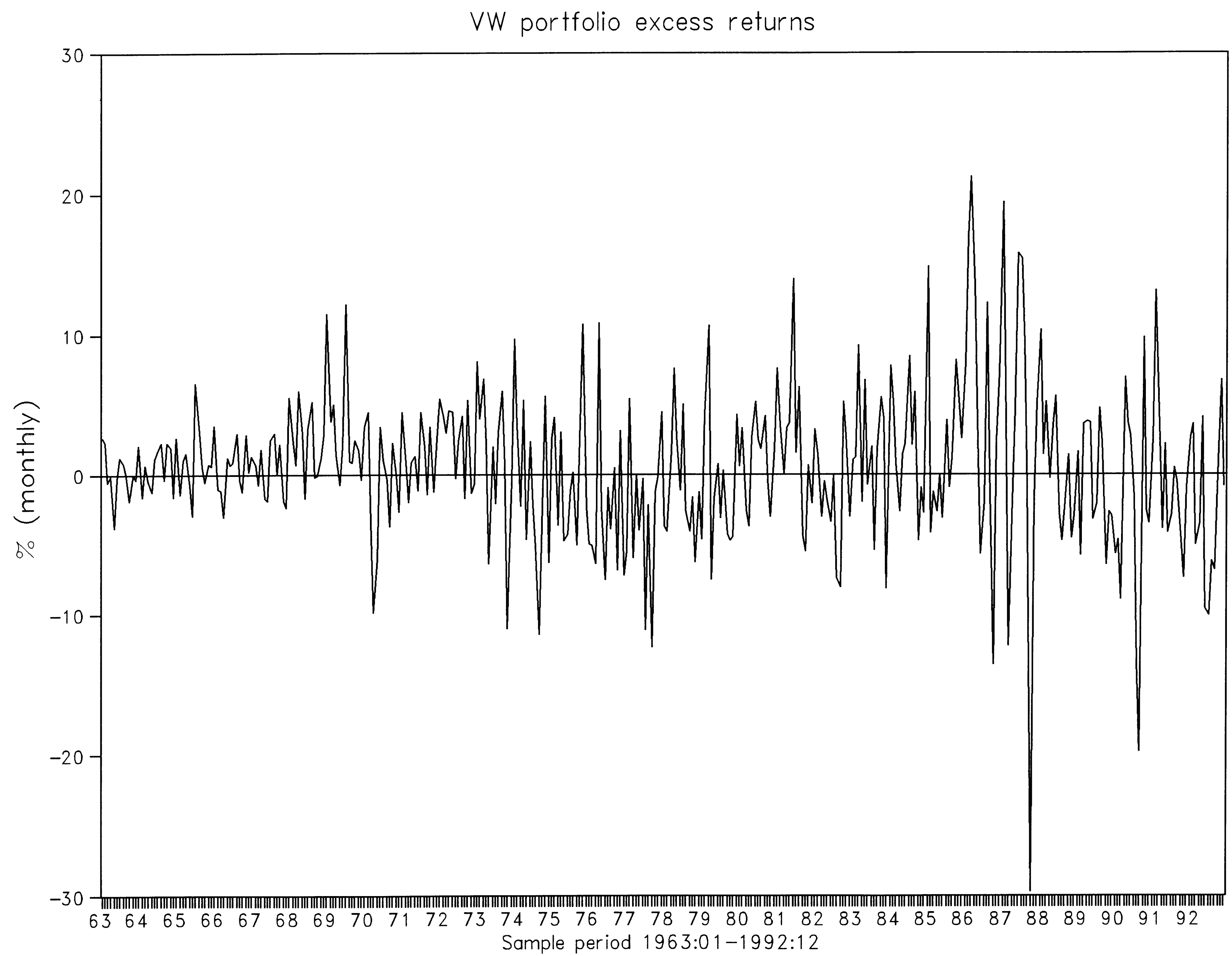

VW portfolio excess returns
% (monthly)
30
20
10
0
-10
-20
-30
63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92
Sample period 1963:01-1992:12

Figure 1

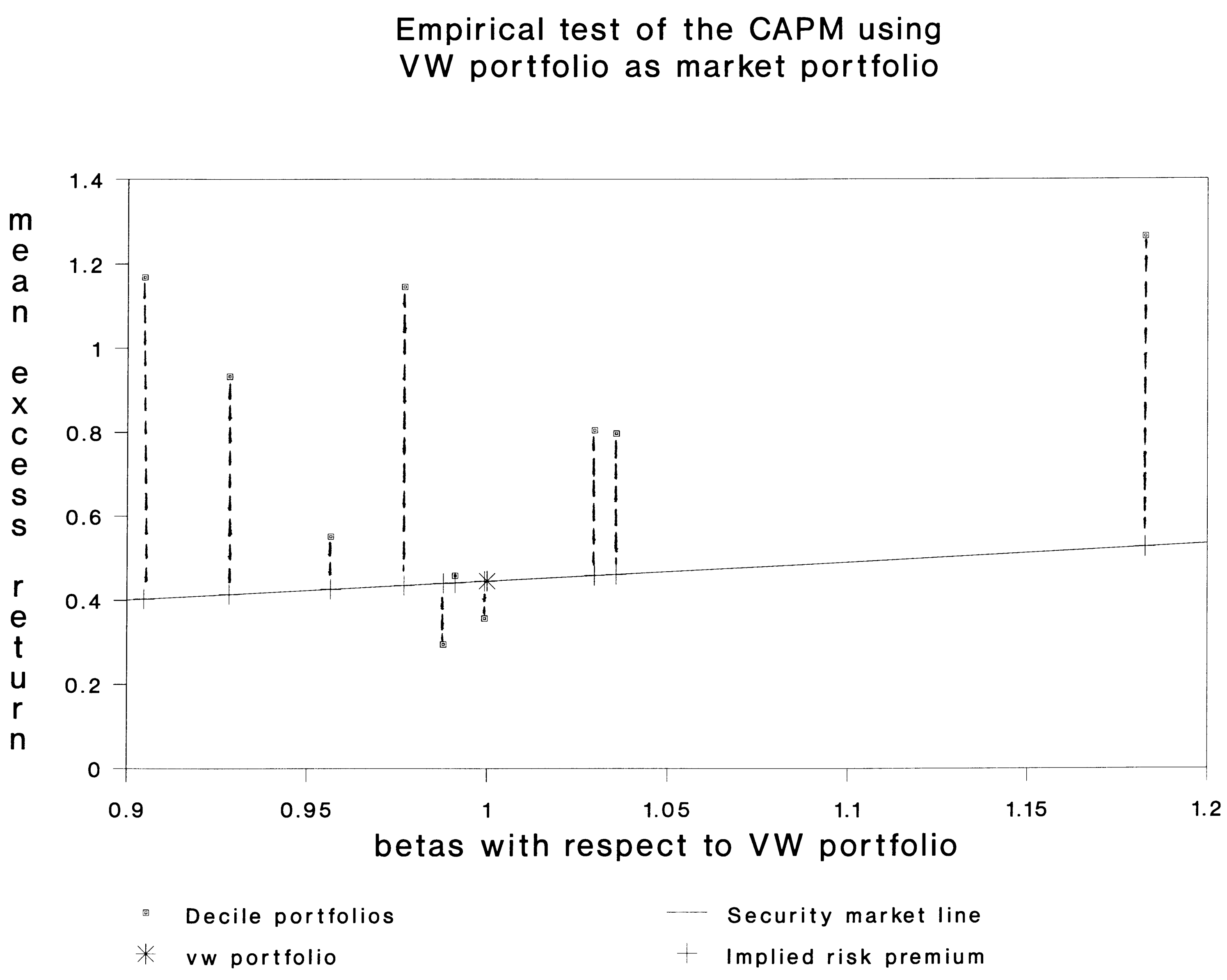

Empirical test of the CAPM using
VW portfolio as market portfolio
mean excess return
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0.9
0.95
1
1.05
1.1
1.15
1.2
betas with respect to VW portfolio
Decile portfolios
vw portfolio
Security market line
Implied risk premium

Figure 2

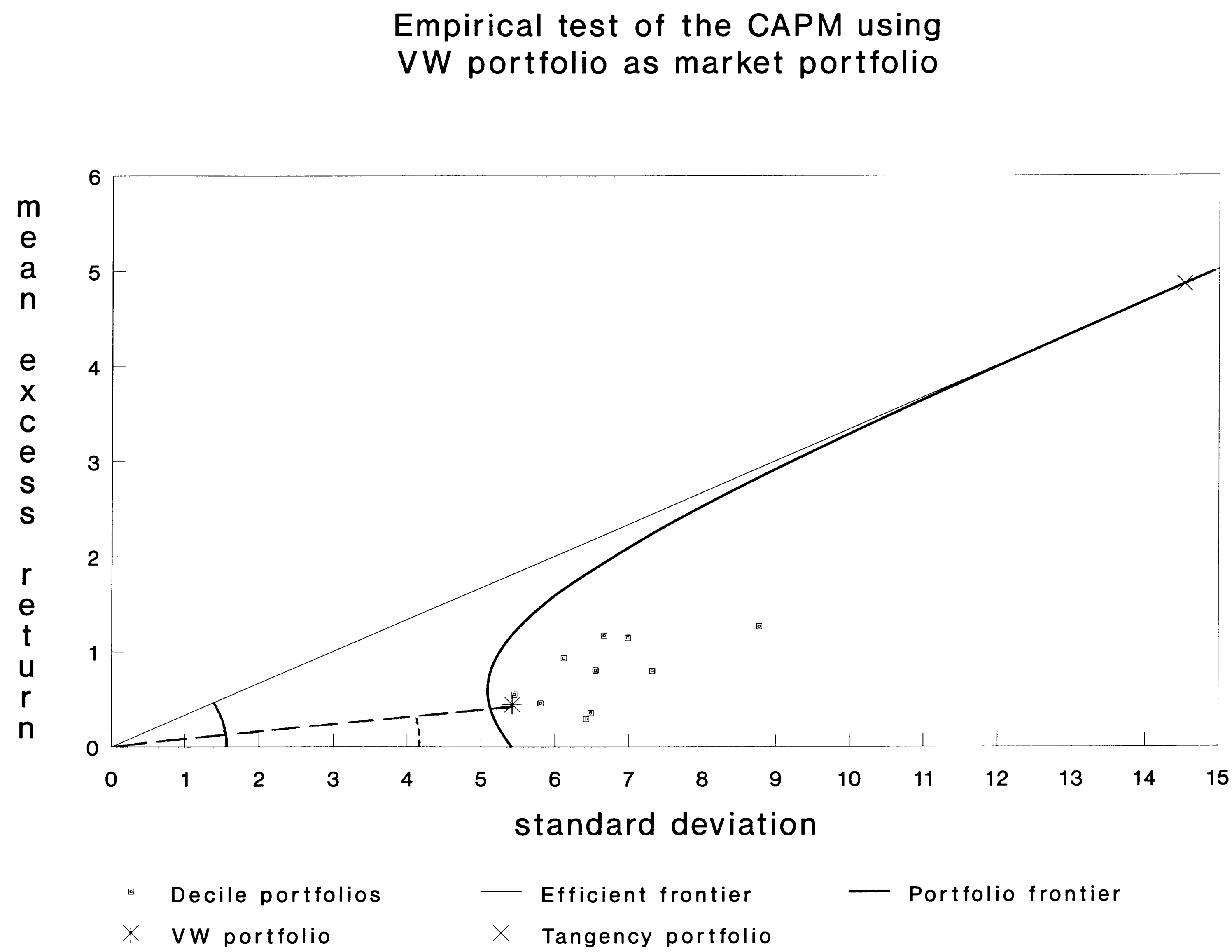
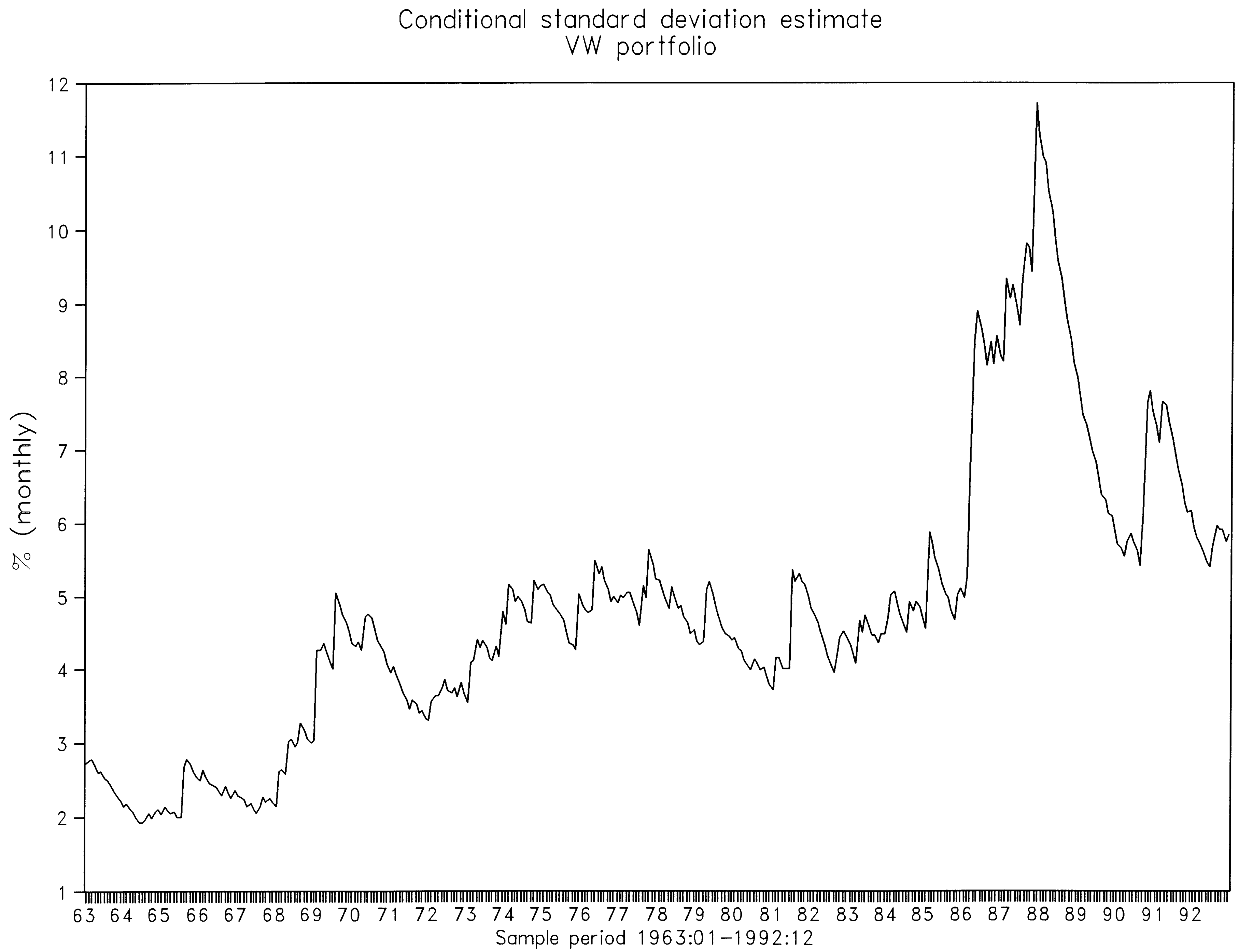

Empirical test of the CAPM using
VW portfolio as market portfolio
mean excess return
standard deviation
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Decile portfolios
Efficient frontier
Portfolio frontier
VW portfolio
Tangency portfolio

Figure 3



Conditional standard deviation estimate
VW portfolio
% (monthly)
1
2
3
4
5
6
7
8
9
10
11
12
63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92
Sample period 1963:01–1992:12

Figure 4