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The role of shifts in the effective tax rate on the cost of equity

Javier Rojo-Suárez, Ana B. Alonso-Conde [*]

Department of Business Administration, Rey Juan Carlos University, Paseo de los Artilleros s/n, Madrid, 28032, Spain

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ABSTRACT

We propose an asset pricing model conditional on the effective tax rate, which allows us to explicitly estimate the impact of shifts in corporate taxes on the expected returns of equities. We evaluate the model using Spanish macro and market data to estimate the time-varying average corporate tax rate and average returns of different anomaly portfolios. Our results show that changes in corporate taxation are strongly explanatory of future stock returns and, consequently, the cost of capital of firms. Furthermore, uncertainty about the future tax burden generally translates into higher expected returns, which results in a lower value of firms.

1. Introduction

Government policies are a key element in promoting entrepreneurship and business development, greatly influencing investment and financing decisions. Furthermore, regulatory changes that result from shifts in the macroeconomic environment have important effects on the profitability of companies and the feasibility of investments. As a logical consequence, financial markets, and more specifically stock exchanges, are directly affected by changes in national regulations, which strongly conditions the cost of equity and, consequently, the value of firms. In particular, while foreseeable regulatory changes often have minor effects on stock returns, unexpected changes in domestic regulation can result in sharp fluctuations in stock prices that lead to changes in expected returns and, consequently, in the equity risk premia (Pastor and Veronesi, 2012). This fact has obvious consequences on the cost of capital and access to financing by companies, thus strengthening the effects of government policies on the growth and competitiveness of firms.

In this framework, tax policies deserve special attention given their relatively high volatility, largely determined by the business cycle and political considerations, as well as their mixed effects on corporate decisions and investment returns (Bernanke, 1983; Hassett and Metcalf, 1999; Bloom, 2009; Johnson and Poterba, 2016; Colombo and Caldeira, 2018; Mumtaz and Theodoridis, 2020; Langenmayr and Lester, 2017; Jacob and Schütt, 2020; Gupta et al., 2014; McDonald, 2002). In this regard, Croce et al. (2012) differentiate three tax-based channels that affect corporate decisions and generate sizeable risk premia, namely: (i) corporate taxes affect earnings and, consequently, the after-tax marginal product of capital, which introduces distortions in investment decisions, (ii) the deductibility of interest on corporate debt, together with insolvency costs and debt adjustment costs that result from leverage, introduces frictions in corporate financing that contribute to explain the effect of tax risk on the cost of equity, and (iii) increases in corporate taxes imply a small but persistent slowdown in long-run productivity growth.

* Corresponding author.
E-mail address: ana.alonso@urjc.es (A.B. Alonso-Conde).

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Table 1
Evidence on the current performance of CAPM.

Reference	Test assets	Sample	Model	R^2 statistic	Passes model evaluation test
Campbell (2018)	25 portfolios BE/ME, 6 risk-sorted portfolios, 18 characteristic- and risk-sorted portfolios and managed versions of these portfolios	1931–1963	Classic CAPM	79%	No (*J*-test)
		1963–2011	Classic CAPM	−20%	No (*J*-test)
Jagannathan and Wang (1996)	100 size-beta portfolios	1963–1990	Classic CAPM	1.35%	No (*HJ*-distance)
			Conditional CAPM	29.32%	No (*HJ*-distance)
			Conditional CAPM with human capital	55.21%	No (*HJ*-distance)
Jagannathan and Wang (2007)	25 size-BE/ME portfolios	1954–2003	Classic CAPM	0%	No (*HJ*-distance)
Lettau and Ludvigson (2001)	25 size-BE/ME portfolios	1963–1998	Classic CAPM	1%	No (X^2 test)
			Conditional CAPM	31%	Yes (X^2 test)
			Conditional CAPM with human capital	77%	Yes (X^2 test)
Lustig and Van Nieuwerburgh (2005)	25 size-BE/ME portfolios and the value-weighted market return	1926–2002	Classic CAPM	28.3%	Not reported
			Collateral-CAPM	87.8%	Not reported
Maio and Santa-Clara (2012)	25 size-BE/ME portfolios	1963–2008	Classic CAPM	−0.42%	Not reported
	25 size-momentum portfolios	1963–2008	Classic CAPM	−0.09%	Not reported
Yogo (2006)	25 size-BE/ME portfolios	1951–2001	Classic CAPM	−62.0%	No (*J*-test)

Building on the seminal contribution by Sharpe (1964) and Lintner (1965) and their capital asset pricing model (hereinafter CAPM), in this paper we adopt the perspective suggested by Cochrane (1996) for considering the effect of conditioning information on asset prices, to explicitly account for the impact of the variations in corporate taxes on discount rates. Specifically, we develop a scaled asset pricing model conditional to the variation on the effective tax rate, which allows us to explicitly estimate the impact of shifts in corporate taxes on the expected returns of firms. In order to evaluate the performance of the model and analyze the effect of changes in corporate taxation on the cost of equity, we compile macro and market data for Spain, for the period from December 1990 to December 2020. Using these data, we estimate the time-varying average corporate tax rate for Spain and the value-weighted average return of different anomaly portfolios, which allows us to conveniently examine the effect of corporate taxation on the equity risk premia. In this regard, it should be noted that, in recent decades, the Spanish economy has undergone some important changes in corporate taxation, which allows us to evaluate the performance of the model more precisely, as well as to analyze more clearly the effects of changes in the effective tax rate on expected returns.

Our paper contributes to the previous research in the following terms. First, to the best of our knowledge, this is the first study to explicitly analyze the effect of changes in corporate taxes on discount rates using the perspective suggested by Cochrane (1996) to overcome the problems arising from the Hansen and Richard (1987) critique. Although other studies determine the unconditional version of the conditional CAPM using different instruments, such as the return on human capital (Jagannathan and Wang, 1996), the consumption-wealth ratio (Lettau and Ludvigson, 2001), the ratio of housing wealth to human wealth (Lustig and Van Nieuwerburgh, 2005), or the Amihud illiquidity measure (Rojo-Suárez et al., 2022), this is the first study to use the average effective tax rate of corporations at the country level for that purpose.

Second, our paper contributes to the literature that relates tax uncertainty and equity risk premia, characterized by providing mixed and often contradictory results. In this regard, Hassett and Metcalf (1999) state that the fact that tax rates remain constant over long periods, changing drastically in specific years, leads to tax uncertainty behaving inversely to other sources of risk, which means that greater tax uncertainty often translates into lower discount rates. Conversely, Sialm (2006) develops a model that considers stochastic taxation in a dynamic general equilibrium setup, which, evaluated on a numerical example, allows the author to conclude that, in general, the higher the tax uncertainty, the higher the required rate of return, and vice versa. Gomes et al. (2009) achieve similar results without explicitly considering the randomness of tax rates.

Third, although Spain is the fourth largest economy in the eurozone by GDP according to International Monetary Fund, it has traditionally attracted limited attention in the asset pricing research. In this context, the empirical validation of the proposed model is not only enriched by the relatively volatile tax burden of the Spanish companies throughout the period under analysis, but also contributes to filling the gap in the understanding of the mechanics of the equity risk premia in countries other than the US. In this regard, McGrattan and Prescott (2005) show that the strong variations experienced by the US and the UK since the 1970s in the relationship between market capitalization and GDP are largely explained by reforms in the tax system, among other regulatory changes. On the other hand, Djankov et al. (2010) study the effects of corporate taxation on a wide range of economic indicators for 85 countries, concluding that increases in the effective tax rate lead to lower domestic and foreign investment and, consequently, lower business activity. Additionally, the authors show that tax rates are closely related to value creation in industrial sectors, while this relationship is less clear in the services sector.

Hereafter, the paper proceeds as follows: Section 2 defines the model under analysis, Section 3 describes the data series and discusses the results, and Section 4 concludes the paper.

2. The model

Although in recent decades the asset pricing literature has been prolific in developing new asset pricing models aimed at better describing the consumption and investment decisions made by economic agents, the classic CAPM continues to be the most widely used asset pricing model for both academic and practical purposes, with expected returns depending on the price of market risk and risk loadings, as follows:

$$E(R^e) = \lambda_{RMRF}\beta_{RMRF} \tag{1}$$

where $E(R^e)$ is the unconditional expectation of the excess return of asset i —i.e. the expected return on a long position in the asset i that is funded by a short position in the risk-free rate—, λ_{RMRF} is the price of market risk (RMRF denotes the market risk premium), and β_{RMRF} is the risk loading on asset i, that is, the slope coefficient of the excess return of asset i on the return on the wealth portfolio, frequently proxied by the return on a broad-based portfolio. In order to simplify the notation, we omit the i subscripts in the equations unless necessary.

In any case, in general, the CAPM has performed poorly in practice. The presence of different market anomalies that allow investors to obtain abnormally high returns, together with the fact that the portfolios that are typically used as a proxy for the wealth portfolio are far from being unconditionally mean-variance efficient, largely explains the empirical failure of the model. In this regard, Table 1 summarizes the main results on the current performance of the CAPM provided by the literature. On this basis, in order to study the informational role of changes in corporate taxation on discount rates, in this paper we propose the following scaled version of the CAPM (hereinafter referred to as scaled CAPM):

$$E(R^e) = \lambda_{RMRF}\beta_{RMRF} + \lambda_T\beta_T + \lambda_{RMRFxT}\beta_{RMRFxT} \tag{2}$$

where λ_T is the price of risk that results from the variations in the effective tax rate of corporations (T), and λ_{RMRFxT} is the price of risk from the comovement of the market portfolio and the effective tax rate, as measured by the second moment of the product between RMRF and lagged T. As in Eq. (1), beta coefficients measure risk exposure to model factors. It should be noted that the last two terms on the right-hand side of Eq. (2) help the model to capture the effects of the conditioning information that arises from the variation in the effective tax rate. Furthermore, this allows the unconditional CAPM to consider potentially time-varying coefficients —both risk prices and betas— of its conditional counterpart.

Eq. (2) can be derived straightforwardly using the stochastic discount factor (SDF) model, which is the dominant approach in contemporary research on asset pricing (Campbell, 2018). According to the SDF model, the price of an asset can be written as the conditional expectation of the product between the SDF —i.e. the intertemporal rate of substitution— and the asset payoff. Accordingly, the pricing function particularized to the case of excess returns —i.e. payoffs with zero price— can be written as follows (Cochrane, 2005):

$$E_t\left(M_{t+1}R^e_{t+1}\right) = 0 \tag{3}$$

where $E_t(\cdot)$ is the expectation conditional on information at time t, and M_{t+1} is the SDF. Rewriting the second moment in Eq. (3) as a function of the covariance between M_{t+1} and R^e_{t+1}:

$$\mathrm{cov}_t\left(M_{t+1}R^e_{t+1}\right) + E_t(M_{t+1})E_t\left(R^e_{t+1}\right) = 0 \tag{4}$$

or equivalently:

$$E_t\left(R^e_{t+1}\right) = -\frac{\mathrm{cov}_t\left(M_{t+1}R^e_{t+1}\right)}{E_t(M_{t+1})} \tag{5}$$

Multiplying and dividing Eq. (5) by the variance of the SDF, $\mathrm{var}_t(M_{t+1})$, results the following beta model:

$$E_t\left(R^e_{t+1}\right) = -\frac{\mathrm{var}_t(M_{t+1})}{E_t(M_{t+1})}\frac{\mathrm{cov}_t\left(M_{t+1}R^e_{t+1}\right)}{\mathrm{var}_t(M_{t+1})} = \lambda_{M,t}\beta_{M,t} \tag{6}$$

where the expected excess return is a function of the price of risk $\lambda_{M,t}$ and the risk loading $\beta_{M,t}$. In order to replace M_{t+1} in Eq. (6) by observable indicators, we can follow Cochrane (2005) to write the SDF as a linear function of a K-dimensional vector of factors, as follows:

$$M_{t+1} = a_t + \mathbf{b}_\mathbf{t}^{'}\mathbf{f}_{\mathbf{t+1}} \tag{7}$$

where a_t and $\mathbf{b_t}$ are parameters and $\mathbf{f_{t+1}}$ is the vector of factors. Substituting Eq. (7) in Eq. (3) and repeating the sequence of operations followed to derive Eq. (6), the following factor model emerges:

$$E_t\left(R^e_{t+1}\right) = \boldsymbol{\lambda}^{'}_{\mathbf{f,t}}\boldsymbol{\beta}_{\mathbf{f,t}} \tag{8}$$

where $\boldsymbol{\lambda}_{\mathbf{f,t}}$ is the K-dimensional vector of risk prices, and $\boldsymbol{\beta}_{\mathbf{f,t}}$ is the K-dimensional vector of risk loadings. Nevertheless, it should be noted that all the previous expressions use conditional moments, which complicates the analytical treatment of Eq. (8). Remarkably, in the case that both the excess return and the SDF are independent and identically distributed (i.i.d.) variables, then there is no difference between conditional and unconditional models and we can suppress the t subscripts in Eq. (8), as follows:

$$E\left(R_{t+1}^{e}\right)=\boldsymbol{\lambda}_{\mathbf{f}}^{\prime}\boldsymbol{\beta}_{\mathbf{f}} \tag{9}$$

However, in general, this assumption is far from realistic, implying that conditional and unconditional models can involve significant differences in explaining the dynamics of asset prices. Consequently, in order to determine the unconditional version of Eq. (8), we follow Cochrane (1996) to assume that its conditional nature stems from the dependence of parameters a_t and $\mathbf{b_t}$ on an instrument z observed at time t. In this context:

$$M_{t+1}=a_t+\mathbf{b}_{\mathbf{t}}^{\prime}\mathbf{f}_{\mathbf{t+1}}=a_0+a_1z_t+(\mathbf{b_0}+\mathbf{b_1}z_t)^{\prime}\mathbf{f}_{\mathbf{t+1}} \tag{10}$$

where a_0, a_1, $\mathbf{b_0}$ and $\mathbf{b_1}$ are parameters. Thus, Eq. (10) assumes that economic agents observe z at time t and, subsequently, configure their expectations about R_{t+1}^{e} to adopt their consumption and investment decisions. Hence, substituting Eq. (10) in Eq. (3), Eq. (8) can be rewritten as follows:

$$E\left(R_{t+1}^{e}\right)=\boldsymbol{\lambda}_{\mathbf{f}}^{\prime}\boldsymbol{\beta}_{\mathbf{f}}+\lambda_{z}^{\prime}\beta_{z}+\boldsymbol{\lambda}_{\mathbf{fxz}}^{\prime}\boldsymbol{\beta}_{\mathbf{fxz}} \tag{11}$$

Building on Eq. (11), Eq. (2) naturally arises from the case where $\mathbf{f}=RMRF$ and $z=T$. Hence, our model assumes that investors first observe the effective tax rate (T) at time t, consistently revise their expectations on asset returns, and finally rework their economic decisions.

For comparison purposes, below we also study the performance of the classic CAPM, as well as that of the Fama-French three- and five-factor models (Fama and French, 1993; Fama and French, 2015). All these models represent special cases of Eq. (9), with the classic CAPM assuming that $\mathbf{f}=RMRF$ and the Fama-French three-factor model implying that $\mathbf{f}^{\prime}=(\,RMRF\quad SMB\quad HML\,)$, where SMB is the small minus big market value factor, and HML is the high minus low book-to-market equity factor. On the other hand, the Fama-French five-factor model adds two extra factors to the Fama-French three-factor model, namely, the excess return of the most profitable stocks minus the least profitable (RMW), and the excess return of firms that invest conservatively minus aggressively (CMA), thus assuming that $\mathbf{f}^{\prime}=(\,RMRF\quad SMB\quad HML\quad RMW\quad CMA\,)$.

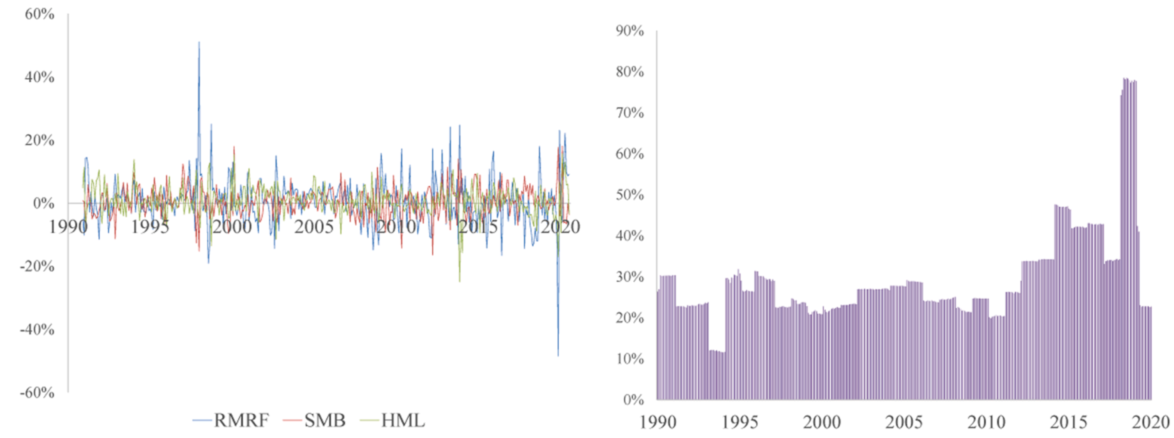
3. Empirical analysis

In this Section we evaluate the empirical performance of the model derived in the previous Section and analyze the effect of changes in corporate taxes on the expected excess returns of different anomaly portfolios in the Spanish equity market. For this purpose, we first describe the data series used in the study and their main summary statistics. We then discuss the results of our model, as well as those provided by the classic CAPM and the Fama-French three- and five-factor models.

3.1. Data series

We compile monthly data series from the Datastream database for all stocks traded on the Spanish equity market, for the period from December 1990 to December 2020. In particular, we compile the following monthly data series: (i) total return index (RI series), which allows us to determine asset returns, (ii) market value (MV series), (iii) market-to-book equity (PTBV series), (iv) total assets (WC02999 series), (v) return on equity (WC08301 series), (vi) dividend yield (DY series), (vii) price-to-earnings ratio (PE series), and (viii) effective tax rate (WC08346 series). To avoid distortions derived from the specificities of special purpose vehicles, among other specific investments, we use the filters suggested by Griffin et al. (2010) for the Datastream database to exclude assets other than ordinary shares from our sample. Hence, our sample comprises 443 companies, including all firms that started trading within the time interval under study, as well as those that were delisted. As a proxy for the risk-free rate, we use the three-month Treasury Bill rate for Spain, as provided by the OECD.

Following common practice, we evaluate model performance using different portfolios formed according to different market anomalies. In this regard, Lewellen et al. (2010) suggest using portfolios that combine mixed sorting variables in order to mitigate the strong factor structure of portfolios typically used in model evaluation, such as those sorted by market equity and book-to-market equity ratio (hereinafter BE/ME ratio). Consequently, we follow Lewellen et al. (2010) to evaluate the models under study on 27 portfolios, as follows: (i) 9 portfolios sorted by market equity and BE/ME ratio (hereinafter size-BE/ME portfolios), (ii) 9 portfolios sorted by dividend yield and price-earnings ratio (hereinafter DY-PE portfolios), and (iii) 9 portfolios sorted by market equity and the effective tax rate (hereinafter size-TR portfolios). We use the methodology suggested by Fama and French (1993) to form all portfolios. In particular, to create size-BE/ME portfolios, each June we allocate all stocks to terciles based on their market equity and, analogously, we allocate stocks in an independent sort to three BE/ME groups. Size-BE/ME portfolios are determined as the intersections of size and BE/ME groups. We calculate value-weighted returns on a monthly basis using the market equity in June to determine portfolio weights. We follow the same approach to form the other two sets of portfolios —DY-PE and size-TR portfolios— using their corresponding sorting variables. Analogously, we follow Fama and French (1993) and Fama and French (2015) to determine the Fama-French factors, RMRF, SMB, HML, RMW and CMA.



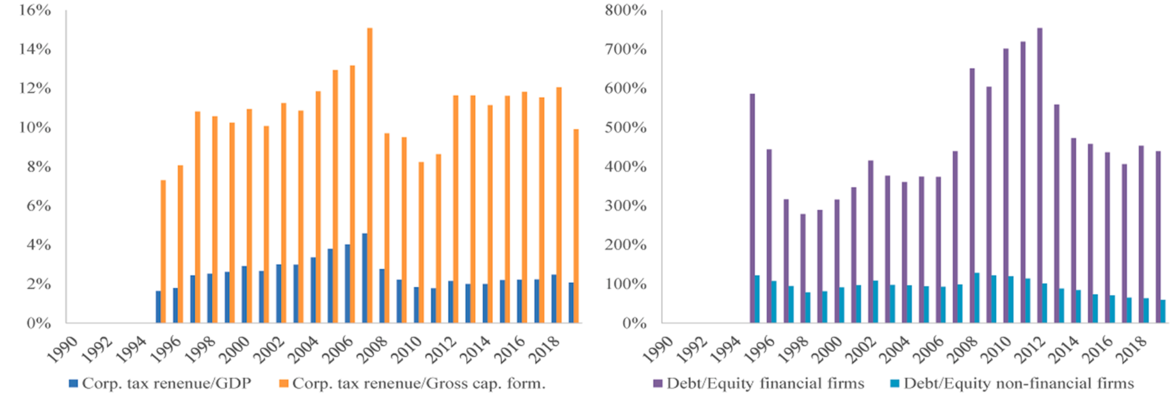
(a) Stock market returns (b) Effective tax rate

Fig. 1. Stock market returns and average effective tax rate of Spanish corporations.

Table 2
Summary statistics.

Panel A: Means and standard deviations											
	BE/ME terciles				PE terciles				TR terciles		
Size	Low	2	High	DY	Low	2	High	Size	Low	2	High
	Means				Means				Means		
Small	0.89	1.31	2.21	Low	0.57	0.48	1.35	Small	1.61	2.65	1.31
2	0.51	0.94	1.34	2	0.48	0.60	0.50	2	1.03	1.33	1.25
Big	0.41	0.64	0.73	High	0.47	0.90	1.02	Big	0.83	0.77	0.67
	St. Dev.				St. Dev.				St. Dev.		
Small	0.51	0.45	0.50	Low	0.41	0.39	1.19	Small	0.77	0.57	0.54
2	0.48	0.29	0.35	2	0.37	0.34	0.35	2	0.34	0.31	0.36
Big	0.33	0.46	0.43	High	0.42	0.31	0.37	Big	0.83	0.33	0.36
Panel B: Correlations											
	BE/ME terciles				PE terciles				TR terciles		
Size	Low	2	High	DY	Low	2	High	Size	Low	2	High
	Correlations with RMRF				Correlations with RMRF				Correlations with RMRF		
Small	0.47	0.44	0.38	Low	0.55	0.48	0.48	Small	0.48	0.25	0.30
2	0.47	0.57	0.52	2	0.52	0.58	0.55	2	0.49	0.48	0.59
Big	0.74	0.74	0.64	High	0.39	0.53	0.55	Big	0.66	0.63	0.65
	Correlations with SMB				Correlations with SMB				Correlations with SMB		
Small	0.08	0.22	0.19	Low	−0.13	−0.06	−0.35	Small	−0.21	0.22	0.22
2	0.10	0.09	0.06	2	−0.20	−0.23	−0.15	2	0.09	0.08	0.04
Big	−0.38	−0.45	−0.31	High	0.03	−0.23	−0.21	Big	−0.48	−0.20	−0.35
	Correlations with HML				Correlations with HML				Correlations with HML		
Small	−0.10	−0.03	0.19	Low	−0.13	−0.02	−0.01	Small	−0.05	0.11	0.07
2	−0.11	0.00	0.17	2	−0.13	−0.04	0.03	2	0.05	−0.05	−0.01
Big	−0.34	−0.01	0.43	High	0.09	0.04	0.11	Big	−0.04	−0.07	−0.05
	Correlations with *T*				Correlations with *T*				Correlations with *T*		
Small	0.10	0.09	0.02	Low	0.08	0.04	−0.03	Small	0.06	0.11	0.08
2	0.04	0.04	0.08	2	0.05	0.03	−0.01	2	0.06	0.08	0.02
Big	0.04	0.01	−0.02	High	0.00	0.06	−0.01	Big	−0.03	0.04	0.05
Panel C: Market factors and effective tax rate											
	RMRF	SMB	HML	RMW	CMA		RF		*T*		RMRFx*T*
Means	0.27	0.57	0.88	0.85	−1.60	Mean	0.31	Mean	29.26	Mean	0.07
St. Dev.	0.40	0.25	0.25	0.54	0.23	St. Dev.	0.34	St. Dev.	11.49	St. Dev.	2.31

Note: All results are determined using monthly data. Means and standard deviations are percentages.



(a) Tax revenue on GDP and gross capital formation (b) Financial leverage of corporations

Fig. 2. Corporate tax revenue and main macroeconomic aggregates.

Regarding the effective tax rate, according to the detail provided by the Datastream database for the WC08346 series, it is determined as the quotient between taxes in the profit and loss account and earnings before taxes. We use the effective tax rate of all companies in our sample to determine the average effective tax rate (T) over time, weighting by market equity. As noted above, our model uses T as the conditioning variable z in Eq. (11), which allows us to transform the conditional model in Eq. (8) into the unconditional CAPM in Eq. (2).

Fig. 1 depicts the monthly returns of the three classic Fama-French factors —i.e. RMRF, SMB and HML— as well as the effective tax rate T over time. On the other hand, Table 2 shows the main summary statistics for both the test assets and the explanatory variables. Subfigure (a) in Fig. 1 shows that the returns of Spanish stocks fit the classic stationary pattern typically followed by equity returns worldwide, while Subfigure (b) shows that the effective tax rate changes primarily every 12 months, consistent with the regulatory basis behind shifts in corporate taxation, with maximum and minimum values of 78.47 % and 11.53 %, respectively. These results are consistent with those shown in Table 2, Panel C, where the average tax rate amounts to 29.26 %, with a standard deviation of 11.49 %.

In order to analyze the interplay between tax collection and the three channels established by Croce et al. (2012) as key determinants of the relationship between corporate taxation and stock returns, Fig. 2, Subfigure (a), relates corporate tax revenue with domestic GDP and gross capital formation, while Subfigure (b) shows the leverage of both financial and non-financial companies in Spain, for the period from December 1990 to December 2020. Fig. 2, Subfigure (a), shows that Spain reaches the maximum tax collection on GDP and gross capital formation in 2007. Remarkably, Subfigure (b) in Fig. 1 shows that this year the effective tax rate in Spain is around 24 %, that is, a relatively low rate compared to the other fiscal years, which is consistent with the rationale outlined by Croce et al. (2012) on the relationship of corporate taxes with productivity and investment.

Regarding the relationship between corporate tax collection and leverage, Subfigure (b) in Fig. 2 shows that, excluding the 2008–2013 period, where the financial crisis resulted in extremely high debt-to-equity ratios due to accumulated losses, in the years following 2013, financial firms exhibit a higher leverage than in the period before 2008. Moreover, Subfigure (b) in Fig. 1 shows that, in the years after 2013, companies bear a significantly higher tax burden than in previous periods. Considering the great importance of the banking sector in the Spanish equity market, this fact is consistent with the incentives that arise from the deductibility of interest on corporate debt, following Croce et al. (2012).

Regarding portfolio returns, Panel A in Table 2 shows that size-BE/ME portfolios fit the classic pattern widely documented in the literature, with portfolios comprising small firms generally providing higher returns than those comprising large companies (size effect), and portfolios comprising firms with high BE/ME ratios generally delivering higher returns than those comprising companies with low BE/ME ratios (value effect). On the other hand, DY-PE and size-TR portfolios do not present any specific pattern other than the aforementioned size effect.

Panel B in Table 2 shows that, in general, our test assets are poorly correlated with the effective tax rate and market factors, except for RMRF, which provides correlations of around 50 % for a large number of portfolios. In any case, it should be noted that these correlations do not determine the explanatory power of the models under study, but it is the correlation between the expected returns and beta coefficients that conditions model performance, as noted in the next Section. Regarding market factors, Panel C in Table 2 shows that the mean return of RMRF amounts to 0.27 % on a monthly basis, that is, 3.24 % on an annual basis, which is fully consistent with the appreciation of the IBEX 35 (the main Stock index of the Spanish equity market) for the period under study.

3.2. Results and discussion

In order to study the effect of changes in corporate taxes on discount rates, as well as to compare the performance of the proposed model with that of other prominent asset pricing models, in this Section we evaluate model performance using the data series described in the previous Section. For that purpose, we estimate the coefficients of all models under analysis mapping the classic two-pass cross-

Table 3
Beta estimates for the scaled CAPM.

Portfolio	β_{RMRF}	β_T	β_{RMRFxT}	Portfolio	β_{RMRF}	β_T	β_{RMRFxT}	Portfolio	β_{RMRF}	β_T	β_{RMRFxT}
Panel A: 9 size-BE/ME portfolios				Panel B: 9 DY-PE portfolios				Panel C: 9 size-TR portfolios			
11	0.74	0.11	-0.37	11	0.95	0.03	-1.08	11	1.34	0.10	-1.15
	(5.80)	(2.70)	(-1.15)		(10.04)	(0.88)	(-4.59)		(7.06)	(1.70)	(-2.44)
12	0.61	0.07	-0.30	12	0.84	0.01	-1.01	12	0.26	0.18	0.30
	(5.25)	(1.96)	(-1.05)		(8.69)	(0.40)	(-4.24)		(1.68)	(3.81)	(0.78)
13	0.84	0.05	-1.00	13	2.22	0.02	-2.23	13	0.53	0.11	-0.32
	(6.40)	(1.33)	(-3.06)		(7.46)	(0.21)	(-3.02)		(3.66)	(2.37)	(-0.89)
21	1.00	0.05	-1.21	21	0.73	0.00	-0.71	21	0.61	0.02	-0.54
	(8.44)	(1.23)	(-4.12)		(8.21)	(0.05)	(-3.21)		(7.20)	(0.63)	(-2.59)
22	0.51	0.03	-0.27	22	0.72	0.00	-0.64	22	0.62	0.03	-0.67
	(7.52)	(1.21)	(-1.58)		(9.15)	(0.04)	(-3.28)		(8.08)	(1.19)	(-3.54)
23	0.60	0.03	-0.41	23	0.43	0.00	0.13	23	0.77	0.01	-0.66
	(7.08)	(1.22)	(-1.96)		(5.11)	(0.03)	(0.61)		(9.27)	(0.43)	(-3.20)
31	0.91	0.01	-0.84	31	0.54	0.00	-0.37	31	1.34	0.01	0.09
	(14.61)	(0.61)	(-5.40)		(4.86)	(0.03)	(-1.34)		(7.44)	(0.14)	(0.19)
32	1.21	0.03	-0.99	32	0.56	0.02	-0.45	32	0.79	0.01	-0.77
	(14.10)	(1.06)	(-4.62)		(7.61)	(0.93)	(-2.45)		(10.96)	(0.40)	(-4.29)
33	0.42	-0.02	0.73	33	0.63	-0.03	-0.34	33	0.88	0.02	-0.80
	(4.48)	(-0.83)	(3.14)		(7.08)	(-1.14)	(-1.52)		(11.40)	(0.78)	(-4.18)

Note: All portfolios are represented with two numbers, the first number being the code for the first sorting variable (with 1 representing the first tercile and 3 the third tercile) and the second number being the code for the second sorting variable (again, 1 represents the first tercile and 3 the third tercile). All results are determined using monthly data.

sectional (CSR) methodology into the generalized method of moments (GMM), as suggested by Cochrane (2005). This procedure not only allows us to simultaneously determine beta and lambda coefficients, but also to correct standard errors for the cross-sectional autocorrelation of the time-series residuals, and for the fact that betas are generated regressors. Accordingly, we estimate model coefficients using the following vector of moments:

$$\mathbf{g_T}(\mathbf{b}) = \left\{ \begin{array}{c} \mathbf{E}\left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right) \\ \mathbf{E}\left[\left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right)\mathbf{X_t}\right] \\ \mathbf{E}\left(\mathbf{R_t^e} - \boldsymbol{\beta}\boldsymbol{\lambda}\right) \end{array} \right\} \tag{12}$$

where $\mathbf{a}$ is the N-dimensional vector of intercepts that result from the time-series regressions, and $\mathbf{X_t}$ is the vector that comprises the factors in vector $\mathbf{f}$, as well as the instrument z when corresponds. For GMM to provide the coefficient estimates that result from the two-pass CSR using ordinary least squares (OLS) as the estimation procedure, we use the following weights for the moments in Eq. (12), where $\mathbf{I}$ denotes the identity matrix:

$$\mathbf{a_T} = \begin{pmatrix} \mathbf{I}_{2N} & \\ & \boldsymbol{\beta}' \end{pmatrix} \tag{13}$$

Hence, the coefficient estimates are determined to satisfy the following moment restrictions:

$$\mathbf{a_T}\mathbf{g_T}(\widehat{\mathbf{b}}) = 0_{3N} \tag{14}$$

Regarding model significance, we estimate standard errors using the following spectral density matrix:

$$\mathbf{S} = \mathbf{E}\left\{ \left[\begin{array}{c} \mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t} \\ \left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right)\mathbf{X_t} \\ \mathbf{R_t^e} - \boldsymbol{\beta}\boldsymbol{\lambda} \end{array} \right] \left[\begin{array}{c} \mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t} \\ \left(\mathbf{R_t^e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{X_t}\right)\mathbf{X_t} \\ \mathbf{R_t^e} - \boldsymbol{\beta}\boldsymbol{\lambda} \end{array} \right]' \right\} \tag{15}$$

At this point, it should be noted that the model proposed in Eq. (2) requires using lagged T to determine the coefficients λ_T, β_T, λ_{RMRFxT}, and β_{RMRFxT}. Accordingly, to establish the number of lags required to maximize the likelihood of the model, we use the Akaike information criterion (AIC), which establishes the optimal number of lags in 4 months. These results may be explained in part by the different dates on which taxes are charged, depending on the closing dates of the accounts for the firms under study.

Table 4
Cross-sectional results for the models under study.

			Market factors					Tax rate				
Row	Model	Intercept	λ_{RMRF}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{T}	λ_{RMRFxT}	R^2	MAE (%)	J-test
1	Classic CAPM	0.010	−0.001							0.002	0.41	49.333
		(2.044)	(−0.087)							−0.222		(0.003)
2	Scaled CAPM	0.007	0.001					0.081	0.001	0.475	0.30	31.987
		(0.996)	(0.093)					(2.533)	(0.198)	−0.084		(0.100)
3	CAPM + T	0.007	0.000					0.076		0.436	0.33	34.232
		(1.013)	(−0.044)					(2.466)		−0.089		(0.081)
4	Fama-French	0.002	0.006	0.007	0.008					0.577	0.26	33.464
	(3 factors)	(0.374)	(0.515)	(2.332)	(2.631)					0.279		(0.073)
5	Fama-French	0.007	−0.004	0.009	0.010	0.002	−0.020			0.724	0.21	25.087
	(5 factors)	(1.326)	(−0.543)	(3.000)	(3.103)	(0.260)	(−2.264)			0.560		(0.243)

Note: The table displays two rows for each model, where the first row shows lambda estimates and the second row shows t statistics. For each model, the column labeled 'R^2' shows OLS and GLS R^2 statistics, in that order. All p-values that result from the J-tests are in parentheses. All results are determined using monthly data.

Based on these specifications, Table 3 shows the beta estimates and *t* statistics that result from the time-series regression of returns on RMRF, *T* and RMRFx*T*. As shown, while most portfolios provide betas greater than 1 for RMRF, in most cases β_T is positive and β_{RMRFxT} is negative, consistent with the fact that taxes induce forces in opposite directions on stock returns, as suggested by Croce et al. (2012). However, it should be noted that, for most portfolios, β_T exhibits a small absolute value, while β_{RMRFxT} is significantly higher. Furthermore, the risk loadings for RMRF and RMRFx*T* are statistically significant for most portfolios, while this is rarely the case for *T*. In this regard, it is important to note that, although the significance of beta coefficients is not directly related to the explanatory power of the model, our results suggest that risk loadings are worse measured for *T* than for the other explanatory variables.

In order to study the explanatory power of the models under analysis, Table 4 shows the results of the cross-sectional regression embedded in Eq. (12). Specifically, for each model, Table 4 displays two rows, where the first row shows lambda estimates —i.e. risk prices— and the second row shows *t* statistics. We evaluate model performance using three different statistics, namely: (i) the cross-sectional R^2 statistic, (ii) the mean absolute error (hereinafter MAE), determined as the difference between the mean return and the result provided by the model, and (iii) the *J*-test for overidentifying restrictions that follows from the fact that Eq. (12) comprises more restrictions than parameters. Regarding the R^2 statistics, for each model we show the results obtained using both OLS (hereinafter OLS R^2 statistics) and the generalized method of moments (hereinafter GLS R^2 statistics), in that order. In this regard, Lewellen et al. (2010) emphasize the convenience of determining both indicators, explaining that, although the OLS R^2 statistic is frequently used in empirical research on asset pricing, the GLS R^2 statistic is more closely related to the mean-variance efficiency of the model's factor-mimicking portfolio and, consequently, implies a more stringent hurdle in model evaluation.

As noted, Table 4 summarizes the main results obtained for all the models under study. In particular, the first row shows the results achieved for the classic CAPM, while the second row shows the estimates for the scaled CAPM, according to Eq. (2). In order to isolate the explanatory power of *T* on a stand-alone basis, the third row shows the results provided by the classic CAPM, including lagged *T* as a factor. Finally, rows 4 and 5 in Table 4 show the results delivered by the Fama-French three- and five-factor models, respectively.

The results in Table 4 highlight two important aspects. First, the classic CAPM (row 1) performs very poorly in the Spanish equity market, providing an OLS R^2 statistic equal to 0.2 % and a MAE of 0.41 %, in line with the results shown in Table 1 for recent tests on CAPM performance. Second, and more important, the scaled CAPM (row 2) allows us to significantly improve the results provided by the model. Thus, with an OLS R^2 statistic of 47.5 % and a MAE equal to 0.3 %, the scaled CAPM leads the former to increase more than 47 % with respect to its classic counterpart, while it leads the MAE to fall 0.11 %, meaning that the average effective tax rate *T* is highly explanatory of the expected returns of the firms traded on the Spanish equity market. Furthermore, our results show that, although RMRFx*T* produces a statistically insignificant and near-zero price of risk λ_{RMRFxT}, the opposite is true for the effective tax rate *T*, which provides a positive and statistically significant lambda coefficient (λ_T). This argument is reinforced by the results shown in row 3 for the classic CAPM augmented by lagged *T*, which still produces good results. In particular, the augmented CAPM provides an OLS R^2 statistic and a MAE of 43.6 % and 0.33 %, respectively, with a price of risk for *T* that remains positive and statistically significant.

Hence, the positiveness of most of the beta coefficients β_T in Table 3, as well as λ_T in Table 4, suggests an increasing relationship between the risk from changes in corporate taxes and expected returns. This fact is further reinforced by the poor performance of the classic CAPM, which indicates that RMRF is scarcely explanatory in the Spanish equity market. Consequently, considering the inverse relationship between present values and expected returns —i.e. discount rates—, our results suggest that uncertainty on future corporate taxation translates into a lower equity value, meaning that the benefits from the deductibility of interest on corporate debt are more than fully offset by the negative effects of corporate taxes on productivity and investment, consistent with Croce et al. (2012).

As noted above, the results in Table 4 allow us to compare the performance of the scaled CAPM with that of the Fama-French three- and five-factor models in rows 4 and 5, respectively. In this regard, Table 4 shows that the Fama-French models exhibit a worse performance in the Spanish equity market than in other markets widely studied in the literature, such as the US equity market, where these models usually provide OLS R^2 statistics greater than 90 %. Regardless of other technical considerations, the shallower depth of the Spanish market, with a sensibly lower number of securities traded, may partially explain the worse performance of the Fama-French models in this context. Thus, while the Fama-French three-factor model provides an OLS R^2 statistic of 57.7 %, this indicator amounts to 72.4 % in the case of the Fama-French five-factor model. Hence, the Fama-French five-factor model is the best performer among the models considered, providing a MAE of 0.21 %. In any case, the fact that the asset pricing literature has not yet unequivocally linked the Fama-French factors to any state variable of special hedging concern to investors, not captured by the market return, means that our results do not reject a fiscal explanation of the Fama-French factors, although the analysis of this point is beyond the scope of this paper.

Regarding the GLS R^2 statistics, although Table 4 shows that this indicator leads to conclusions similar to those provided by the OLS R^2 statistic and the MAE, with the Fama-French three- and five-factor models being the best performers among those considered in Table 4 and the classic CAPM producing the worst results, in all cases the GLS R^2 statistics are lower than their OLS counterparts, which is especially remarkable for the scaled CAPM and the augmented CAPM (rows 2 and 3 in Table 4, respectively). This means that while the effective tax rate comprises useful pricing information that helps both scaled CAPM and augmented CAPM to perform significantly better than the classic version of the model, the factor-mimicking portfolios tied to those models are far from mean-variance efficient, which is a logical consequence of the large number of variables other than the effective tax rate that economic agents consider when making their consumption and investment decisions.

Additionally, the results in Table 4 show that the *J*-test for overidentifying restrictions does not reject models 2–5, that is, the scaled CAPM, the classic CAPM augmented by lagged *T*, and the Fama-French models, with only the classic CAPM being strongly rejected by the *J*-test. However, it should be noted that the Fama-French five-factor model and the scaled CAPM are the models that provide the highest *p*-value of all those considered, in that order.

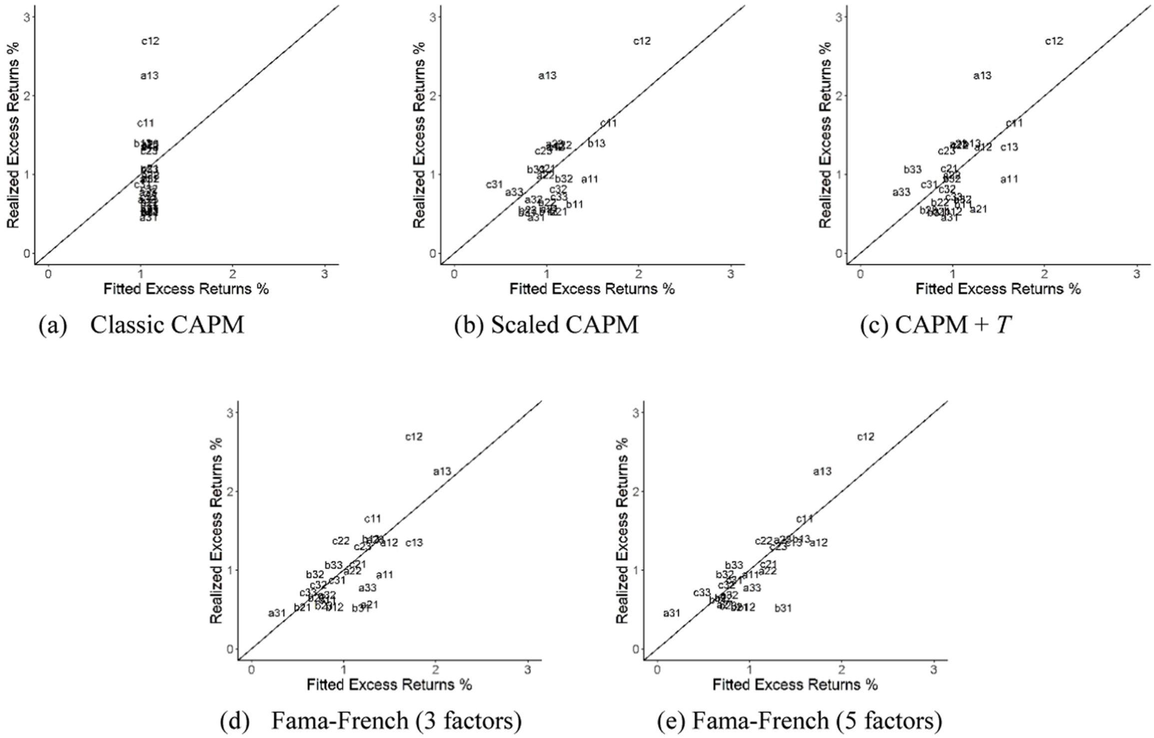


Fig. 3. Real values versus fitted values.
Note: We depict each portfolio using a code with a letter and two numbers. Letter 'a' corresponds to size-BE/ME portfolios, letter 'b' corresponds to DY-PE portfolios, and letter 'c' corresponds to size-TR portfolios. The numbers denote terciles, the first number being the code for the first sorting variable (with 1 representing the first tercile and 3 the third tercile) and the second number being the code for the second sorting variable (again, 1 represents the first tercile and 3 the third tercile). All results are determined using monthly data.

In order to gain further understanding of the pricing errors produced by the models under analysis, Fig. 3 relates the average returns of the 27 portfolios considered in our study with the estimates provided by the five models represented in Table 4. Consequently, the smaller the distance of the data points from the 45-degree angle axis, the better the performance of the model, and vice versa. Consistent with the results in Table 4, Fig. 3 shows that the scaled CAPM, the classic CAPM augmented by lagged *T*, and the Fama-French five-factor model are the best performers of all the models under study. Moreover, Subfigure (a) in Fig. 3 shows that the market risk premium cannot capture the variation in expected returns across assets, while Subfigures (b) and (c) show that the price of risk from changes in corporate taxes, λ_T, is highly explanatory for many of the portfolios under analysis. Hence, our results are consistent with a strong positive relationship between the effective tax rate of corporations and expected returns, meaning that the greater the tax uncertainty, the lower the equity value, and vice versa.

4. Conclusions

Although part of the asset pricing literature analyzing the effects of corporate taxes on stock returns has focused largely on the benefits of tax deductibility of interest on corporate debt, generally concluding that corporate taxes reduce discount rates and, consequently, imply higher equity values, the effects of corporate taxes on investment decisions and firm productivity involve a particular complexity that has led to mixed conclusions. Building on the unconditional version of a conditional CAPM that explicitly accounts for the conditioning information embedded in effective tax rates, our results provide three main conclusions. First, the effective tax rate paid by corporations is strongly explanatory of expected excess returns in the Spanish equity market. In particular, our scaled CAPM allows the model to increase the cross-sectional R^2 statistic up to 47% with respect to the classic CAPM, and the MAE to decrease by 0.11 %, on a monthly basis.

Second, our results suggest that risk exposure to changes in corporate taxation has a positive effect on expected returns, so that the greater the variability in the tax treatment of profits, the higher the expected returns, the higher the cost of equity capital and, consequently, the lower the asset prices. Although the specific nature of tax uncertainty leads part of the literature to reach opposite conclusions (Hassett and Metcalf, 1999), our results are consistent with the studies highlighting the presence of a positive relationship between tax risk and discount rates (Sialm, 2006; Gomes et al., 2009). Thus, our results reinforce the importance of analyzing the effects of government policies as uncertainty in the tax rate regulation has effects on the cost of equity capital, the value of firms and, therefore, on firm growth and competitiveness.

Third, our results show that the effective tax rate allows the scaled CAPM to provide results relatively close to those delivered by the

Fama-French three-factor model in the Spanish equity market. Accordingly, these results not only illustrate the relevance of fiscal policy, and particularly tax policy, in the investment decision-making process of corporations, but are also consistent with a tax-related explanation of the strong explanatory power of Fama-French factors.

Considering these results, future research should deepen the knowledge on the impact of the conditioning information that results from tax changes on asset prices. Specifically, our approach can be enriched by the theoretical environment defined by Croce et al. (2012) to determine what fraction of the explanatory power of tax rates stems from investment, financing and productivity channels. Moreover, our model may benefit from the contributions made by the macroeconomic learning literature (Pastor and Veronesi, 2009; Johannes et al., 2016; Vázquez and Aguilar, 2021), where time-varying betas can be explained by the fact that economic agents ignore the underlying model structure, but they learn about it by observing data. Additionally, future research should address the extent to which the model results are sensitive to the methodology followed to determine the effective tax rate or depend on firm characteristics (Graham et al., 2017; Dyreng et al., 2017).

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Declaration of competing interest

None.

Data availability statement

Research data are available upon request.

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