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Trade integration and research and development investment as a proxy for idiosyncratic risk in the cross-section of stock returns

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ABSTRACT

Although consumption-based asset pricing constitutes a solid body of work for the purpose of relating asset prices and macroeconomics, most empirical tests put into question the representative investor perspective. Furthermore, most approaches accounting for untraded risks, such as the Constantinides-Duffie model, face the problem of correctly quantifying idiosyncratic risk. In this paper we exploit the strong relationship of income inequality with trade openness and research and development (R&D) investment to proxy the cross-sectional variance of consumption growth by the growth rate of imports plus exports (trade openness) and the growth of the domestic expenditure in R&D. Moreover, we use these variables as a part of the information set used by investors to determine the unconditional version of the conditional consumption-capital asset pricing model (CCAPM). Our results show that both trade openness and R&D investment allow the linearized version of the Constantinides-Duffie model and the conditional CCAPM to greatly outperform the classic CCAPM for different sorts of stock portfolios, contributing significantly to reducing pricing errors. Hence, our results constitute a step forward in the attempt to relate asset prices and income inequality in a tractable way.

1. Introduction

The consumption-capital asset pricing model (hereafter, CCAPM), initially developed by Lucas (1978) and Breeden (1979), constitutes a powerful tool for analyzing the relationship between asset pricing and macroeconomics in a tractable and parsimonious way, where the marginal utility of economic agents is assumed as the key determinant of asset prices. Although the model is easily adaptable to different assumptions related to the dynamics of investor behavior, it has traditionally been studied from the perspective of a representative agent, where individual consumption is proportional to aggregate consumption, and the market completeness allows investors to perfectly insure themselves against idiosyncratic risk. However, despite its solid theoretical background, the CCAPM has generally performed poorly in empirical research, giving rise to different puzzles widely studied in the asset pricing literature, such as the equity premium puzzle or the risk-free rate puzzle (Mehra and Prescott, 1985; Weil, 1989). Importantly, these puzzles remain unexplained for most industrialized countries, including Japan (Kocherlakota, 1996; Mehra and Prescott, 2003; Noda, 2013).

In order to overcome these limitations, part of the asset pricing literature relaxes the assumption of market completeness, causing

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factors other than the aggregate consumption growth become relevant for pricing assets. In this regard, the model proposed by Constantinides and Duffie (1996) is especially remarkable. Considering the effect of uninsurable, persistent and heteroskedastic labor income shocks on assets returns, the authors derive a stochastic discount factor (hereinafter SDF or pricing kernel) that not only depends on the aggregate consumption growth, but also on the cross-sectional variance of consumption growth across economic agents. Nevertheless, the lack of micro data on consumer preferences is a major drawback of the model for practical applications (Schmidt, 2014; Constantinides and Ghosh, 2017; Ravina, 2019; Chen et al., 2020).

Based on the model proposed by Constantinides and Duffie (1996), in this paper we study the explanatory power of trade openness and research and development (R&D) investment as proxies for idiosyncratic risk, for the cross-sectional behavior of stock returns on the Japanese equity market. Although previous research on asset pricing uses different approaches to account for agent heterogeneity, a large part of the literature uses data from the Consumer Expenditure Survey, as provided by the US Bureau of Labor Statistics, to estimate the cross-sectional variance of consumption growth (Cogley, 2002; Brav et al., 2002; Vissing-Jorgensen, 2002; Jacobs and Wang, 2004; Balduzzi and Yao, 2007; Kubota et al., 2008). Furthermore, according to OECD estimates, the Gini coefficient for disposable income, which is widely used to measure income inequality, increased in Japan from 0.28 in 1985 to 0.33 in 2006. This increase (18%) is large compared to other OECD countries (9% on average). Therefore, following Constantinides and Duffie (1996) and OECD (2011), we assume that the dispersion of the cross-sectional distribution of income and consumption stems from income inequality, as measured by trade openness and R&D investment, where trade openness is determined as the growth rate of imports plus exports and R&D investment is determined as the growth rate of the gross domestic expenditure in research and development.

In order to study the performance of the model, we adopt two different perspectives. First, we test the linearized version of the Constantinides-Duffie model in its unconditional form, which can be written as a beta model with the aggregate consumption growth and income inequality, as measured either by trade openness or investment in R&D, as model factors. Second, we follow Cochrane (1996) to determine the unconditional version of the conditional CCAPM, using trade openness and R&D investment as instruments to parameterize the SDF of the model. For comparative purposes, we relate all results with those provided by the classic CCAPM. We test all models on three sets of portfolios, namely, 25 size-book-to-market equity portfolios (hereinafter size-BE/ME portfolios), 20 momentum portfolios and 61 industry portfolios.

This paper contributes to the literature on asset pricing and income inequality in the following terms. First, to the best of our knowledge, this is the first study to explicitly use trade openness and R&D investment as proxies for idiosyncratic risk in the analysis of the cross-sectional behavior of the Japanese equity market. For example, Xu and Zhang (2004) examine the relationship between the expected returns and the R&D intensity of Japanese firms, concluding that in the period 1993–2000 average returns and R&D intensity are significantly positively related. However, the authors completely ignore conditioning information and do not evaluate the explanatory power of trade openness. Endoh (2018) studies the effect of import competition on the wages of the Japanese manufacturing sector, for the period from 1998 to 2013. The author concludes that import competition does not reduce the wages of unskilled workers, but it increases the skill premia of workers with college degrees or those in managerial and professional positions. However, it should be noted that the author uses panel data from the Basic Survey on Wage Structure and the Basic Survey of Japanese Business Structure and Activities, focusing exclusively on the manufacturing sector.

Second, our research examines the informativeness of income inequality from a dual perspective, namely: (i) when trade openness and R&D investment are used as proxies for the cross-sectional variance of consumption growth in the linearized version of the Constantinides-Duffie model, and (ii) when idiosyncratic risk, as measured by trade openness and R&D investment, is used as an instrument in determining the unconditional version of the conditional CCAPM. Importantly, Campbell and Cochrane (2000) argue that, in general, conditional asset pricing models will perform significantly better than their unconditional counterparts when habit formation is present. In this framework, our research allows us to analyze the extent to which income inequality can help the conditional CCAPM avoid an explicit specification of habit formation preferences.

Third, unlike most research on the cross-sectional behavior of international expected returns, which often adopts the perspective of a US investor investing internationally (see for example Fama and French (2017)), in this paper we take the perspective of a Japanese investor that invests domestically, thus mitigating the distortions that result from the variation in exchange rates. In this regard, it should be noted that a large part of the contemporary literature on asset pricing uses return series from public databases, such as those provided online by Kenneth French. However, these series do not fit our assumption of a Japanese investor, as most of these databases are denominated in dollars. Therefore, we fully generate all return series for the portfolios under study, using market data compiled from the Datastream database and following the procedure suggested by Fama and French (1993) to create all portfolios.

The remainder of the paper is organized as follows. Section 2 summarizes the main contributions of the recent literature analyzing the effects of idiosyncratic risk on asset prices and income inequality. Section 3 defines the models under analysis. Section 4 describes the data and shows the main descriptive statistics. Section 5 discusses the results. Section 6 concludes the paper.

2. Literature review

As noted above, a large part of the literature analyzing the effect of idiosyncratic risk on asset prices uses data from the Consumer Expenditure Survey to estimate the cross-sectional variance of consumption growth. In this regard, Cogley (2002) finds that the cross-sectional variance of the log consumption growth is only weakly correlated with stock returns. Moreover, the author shows that consumption growth together with its cross-sectional variance results in small equity premia when risk aversion is low. In contrast, Brav et al. (2002) find that the weighted average marginal rate of substitution of individual households helps the CCAPM explain the equity risk premium for relative risk aversion coefficients ranging from 3 to 4. Jacobs and Wang (2004) use higher-order moments of consumption growth in a linear pricing kernel to develop a two-factor CCAPM that significantly outperforms the classic capital asset pricing model (CAPM).

On the other hand, Balduzzi and Yao (2007) suggest using the change in the cross-sectional variance of log consumption rather than the cross-sectional variance of log consumption growth to capture consumer preferences. However, the authors show that, in that case, the pricing kernel still requires a high relative risk aversion coefficient –greater than 9– to explain the equity premium. For the specific case of the Japanese equity market, Kubota et al. (2008) show that monthly, income-decile consumption data from the Japanese Family Income and Expenditure Survey do not allow the CCAPM to explain the equity premium puzzle.

Regarding income inequality, according to the OECD (2011) and Dabla-Norris et al. (2015), technological advances are a key determinant of rising income inequality in the OECD countries, explaining nearly a third of the widening gap between the 10th and 90th income percentiles over the past 25 years. Indeed, technological changes and automation can disproportionately raise the demand for capital and skilled labor at the cost of employment in low-skilled sectors (Acemoglu, 1998; Card and DiNardo, 2002). Furthermore, following Freeman (2009), advances in technology also go hand-in-hand with the fragmentation of economic activities and production offshoring.

Nevertheless, following Milanovic and Squire (2005) and Papageorgiou et al. (2008), income inequality is not only related to technological progress, but also to globalization. According to OECD national accounts data, the share of world trade in global Gross Domestic Product (GDP) increased from about a third to more than a half in the 40 years to 2019. The Stolper-Samuelson theorem (Stolper and Samuelson, 1941) states that trade should benefit relatively abundant factors, meaning that in developed countries, with an abundance of skilled labor, the wages of skilled workers should rise relative to those of unskilled workers, so inequality should increase with trade. The opposite is expected to happen in developing countries, where inequality should decrease with trade. However, recent literature based largely on firm heterogeneity suggests that income inequality often increases with trade openness (Egger and Kreickemeier, 2009; Verhoogen, 2008; Amiti and Davis, 2008). Thus, disentangling the impact of trade openness on income inequality is a difficult task as it depends not only on the relative abundance of labor, but also on firm-specific characteristics (Harrison et al., 2010).

3. Methodology

Following Constantinides and Duffie (1996), we assume an economy in which individual investors i have different consumption levels C_{it} at time t. Individual consumption growth is determined by an independent, idiosyncratic normal distributed shock η_{it}, satisfying:

$$ln\left(\frac{C_{it+1}/C_{t+1}}{C_{it}/C_t}\right) = \eta_{it+1}y_{t+1} - \frac{1}{2}y^2_{t+1} \tag{1}$$

where C_t is the aggregate consumption and $y^2{}_{t+1}$ is the cross-sectional variance of consumption growth. As noted by Grossman and Shiller (1982), when idiosyncratic shocks η_{it+1} are uncorrelated with asset returns, they have no effect on prices. Conversely, when idiosyncratic shocks are correlated with asset returns, consumers can get rid of them by trading away consumption. In any case, according to Constantinides and Duffie (1996), assuming a nonlinear utility function, consumption shocks turn into marginal utility shocks, and hence can generate an equity premium. In this framework, assuming power utility, Constantinides and Duffie (1996) show that the investor's first-order condition results in the following pricing function, particularized to the case of excess returns, that is, assets with price zero that represent a long position in an asset that is funded by a short position in another asset:

$$\mathbf{E_t}\left\{\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left[e^{\frac{\gamma(\gamma+1)}{2}y^2_{t+1}}\right]\mathbf{R^e_{t+1}}\right\} = \mathbf{0}_N \tag{2}$$

where $\mathbf{E_t}$ is the expectation conditional on all information available at time t, β is the subjective discount factor, γ is the coefficient of relative risk aversion, and $\mathbf{R^e}_{\mathbf{t+1}}$ is a N-dimensional vector of excess returns. More synthetically, expression (2) can be written as follows:

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

where m_{t+1} is the SDF or pricing kernel. Importantly, the cross-sectional variance of the log consumption growth $y^2{}_{t+1}$ is assumed to be negatively correlated with aggregate consumption, meaning that idiosyncratic risk increases in economic downturns and decreases in economic upturns. This assumption reinforces the countercyclical nature of the SDF, helping the model to mitigate the equity premium puzzle.

The SDF in expression (3) can be linearized in a K-dimensional vector of factors, as follows (for a complete review of the procedures that allow linearizing the SDF of any asset pricing model see Cochrane (2005) (pp. 161–165)):

$$\mathbf{E_t}\left[\left(a_t + \mathbf{b_t'}\mathbf{f_{t+1}}\right)\mathbf{R^e_{t+1}}\right] = \mathbf{0}_N \tag{4}$$

where a_t and $\mathbf{b_t}$ are parameters, and $\mathbf{f_{t+1}}$ is the vector of pricing factors. Therefore, any linear asset pricing model can be identified by a specific vector of factors $\mathbf{f_{t+1}}$. For example, the classic CCAPM assumes that $\mathbf{f_{t+1}} = \Delta C_{t+1}$, where ΔC_{t+1} denotes the aggregate consumption growth. Furthermore, according to expression (2), expression (4) allows us to write the vector of factors of the linearized version of the Constantinides-Duffie model as a function of aggregate consumption growth and the cross-sectional variance of the log consumption growth, as follows:

$$\mathbf{f}_{t+1} = \left(\Delta C_{t+1} \quad y_{t+1}^2\right)' \tag{5}$$

The SDF model in expression (4) can easily be transformed into a beta model, which is the most common representation in empirical research on asset pricing. Specifically, according to the Equivalence Theorem (Dybvig and Ingersoll, 1982; Hansen and Richard, 1987; Roll, 1977; Ross, 1978), we can rewrite expression (4) as follows:

$$\mathbf{E}_t\left(\mathbf{R}_{t+1}^{e}\right) = \beta_t\left(\mathbf{R}_{t+1}^{e}, \mathbf{f}_{t+1}\right)\lambda_t(\mathbf{f}_{t+1}) \tag{6}$$

where $\beta_t(\mathbf{R}_{t+1}{}^{\mathbf{e}}, \mathbf{f}_{t+1})$ is the matrix of slopes of the regression of excess returns on factors $\mathbf{f}_{t+1}$, and $\lambda_t(\mathbf{f}_{t+1})$ is the vector of prices of risk. Analogously, the unconditional version of expression (6) can be written as follows, under the assumption that model coefficients are constant over time:

$$\mathbf{E}\left(\mathbf{R}_{t+1}^{e}\right) = \beta\left(\mathbf{R}_{t+1}^{e}, \mathbf{f}_{t+1}\right)\lambda(\mathbf{f}_{t+1}) \tag{7}$$

As noted above, we use both trade growth, as measured by exports plus imports, and investment growth in R&D –i.e. the gross domestic expenditure in research and development– as proxies for the cross-sectional variance of the log consumption growth. Accordingly, below we evaluate the performance of expression (7) assuming the following vectors of factors:

$$\left.\begin{array}{rl} \text{Model 1}: & \mathbf{f}_{t+1} = \Delta C_{t+1} \\ \text{Model 2}: & \mathbf{f}_{t+1} = \left(\Delta C_{t+1} \quad \Delta T_{t+1}\right)' \\ \text{Model 3}: & \mathbf{f}_{t+1} = \left(\Delta C_{t+1} \quad \Delta RD_{t+1}\right)' \end{array}\right\} \text{ Unconditional models} \tag{8}$$

where ΔT_t is the growth of trade in goods and services and ΔRD_t is the growth rate of gross domestic expenditure in research and development.

In any case, part of the asset pricing literature attributes the poor explanatory power of the CCAPM and the classic CAPM to the time-varying nature of the coefficients in expression (4) and, more particularly, the fact that a conditional asset pricing model does not necessarily implies an unconditional asset pricing model. In this regard, Hansen and Richard (1987) develop rigorous proofs and important technical assumptions on the role of conditioning information, concluding that the fact that the researches cannot observe agents' information sets implies that the conditional linear factor models are not testable. Nevertheless, based on the Hansen and Richard (1987) critique, Cochrane (1996) suggests a partial solution for testing dynamic, conditional factor models that allows the author to parameterize the SDF, writing it as a function of different instruments, which represent coarser information sets than those used by investors. In any case, for instruments to improve the explanatory power of the model, they must forecast returns or the SDF (i. e. macroeconomic variables) (Cochrane, 2005) (pp. 135). Therefore, based on the empirical evidence that underlines the predictive power of both trade openness and R&D investment (Frankel and Romer, 1999; Wacziarg and Horn Welch, 2008; Ciccone and Jarociński, 2010; Hsu, 2009; Hsu and Huang, 2010; Hirshleifer et al., 2013), additionally to Models 1–3 in expression (8), we also study the explanatory power of these variables when used as instruments. Thus, following Cochrane (1996), we assume that the time-varying nature of the model coefficients results from their dependence on an instrument z observable at time t. In that case, we can rewrite expression (4) in an unconditional form, as follows:

$$\mathbf{E}\left\{\left[(a_0 + a_1 z_t) + (\mathbf{b_0} + \mathbf{b_1} z_t)'\mathbf{f}_{t+1}\right]\mathbf{R}_{t+1}^{e}\right\} = \mathbf{0}_N \tag{9}$$

Expression (9) allows us to transform the unconditional beta model in expression (7) into the following equation:

$$\mathbf{E}\left(\mathbf{R}_{t+1}^{e}\right) = \beta\left(\mathbf{R}_{t+1}^{e}, \mathbf{f}_{t+1}\right)\lambda(\mathbf{f}_{t+1}) + \beta\left(\mathbf{R}_{t+1}^{e}, z_t\right)\lambda(z_t) + \beta\left(\mathbf{R}_{t+1}^{e}, z_t\mathbf{f}_{t+1}\right)\lambda(z_t\mathbf{f}_{t+1}) \tag{10}$$

As we can observe from expressions (7) and (10), conditioning information adds two extra terms to the SDF, given by the lagged instrument z_t and the product of the lagged instrument with factors $z_t\mathbf{f}_{t+1}$. Accordingly, in addition to Models 1–3 shown in expression (8), below we use both trade openness and investment in R&D as a part of the information set used by investors, to define the following vector of factors, in which we call the conditional CCAPM hereinafter:

$$\left.\begin{array}{rl} \text{Model 4}: & \mathbf{f}_{t+1} = \left(\Delta C_{t+1} \quad \Delta T_t \quad \Delta T_t \Delta C_{t+1}\right)' \\ \text{Model 5}: & \mathbf{f}_{t+1} = \left(\Delta C_{t+1} \quad \Delta RD_t \quad \Delta RD_t \Delta C_{t+1}\right)' \end{array}\right\} \text{ Conditional models} \tag{11}$$

4. Variables and data

We test all models defined in the last section on different sets of portfolios, which comprise all stocks traded on the Japanese equity market, from January 1983 to December 2019. Specifically, we consider all stocks traded on the Tokyo Stock Exchange, Osaka Exchange, Fukuoka Stock Exchange, Nagoya Stock Exchange and Sapporo Securities Exchange. We compile all stock data from the Datastream database. Particularly, we collect the following data series, on a monthly basis: (i) total return index (RI series), (ii) market value (MV series), (iii) market-to-book equity (PTBV series), and (iv) primary SIC codes. Following Griffin et al. (2010), we exclude non-common equity securities from Datastream data. Additionally, we remove all companies with less than 12 observations in RI series for the period under analysis. Hence, our sample comprises 5627 stocks, considering all companies that started trading or were delisted in the period under analysis. We use the three-month Treasury Bill rate for Japan, as provided by the OECD database, as a proxy for the risk-free rate.

Given the strong factor structure of the 25 size-BE/ME portfolios, typically used in cross-sectional research on asset pricing, Lewellen et al. (2010) suggest using additional portfolios sorted by other variables to test asset pricing models. Consequently, as noted above, in addition to size-BE/ME portfolios, we use 20 momentum portfolios and 61 industry portfolios to test the models under consideration. All these portfolios are formed following the procedure suggested by Fama and French (1993), except the momentum portfolios. In this case, while Fama and French (1993) rebalance momentum portfolios on a monthly basis, we rebalance our portfolios in June of each year. As shown below, this allows us to significantly increase the spread between past winners and past losers and, consequently, better evaluate the performance of the models under study. All data are publicly available at Rojo-Suárez and Alonso-Conde (2021).

We compile all macroeconomic data from the OECD Statistics database. Regarding consumption data, the limited availability of nondurable goods and services series for Japan motivates the use of total consumption of households series. In any case, it is worth mentioning that Parker and Julliard (2005) show that the total consumption of households fits the cross-section of expected returns better than consumption in nondurables and services. On the other hand, we also collect exports, imports and R&D investment for Japan from the OECD Statistics section (datasets 'P6: Exports of goods and services' and 'P7: Imports of goods and services', from the OECD Gross domestic product (GDP) Statistics, and 'Gross Domestic Expenditure on R&D', Main Science and Technology Indicators, respectively).

Table 1 shows the main summary statistics for both test assets and explanatory variables. As shown in Panel A, in general, the size effect –the fact that small stocks tend to have higher returns than big stocks– works as expected. However, the value effect –the fact that high BE/ME stocks usually provide higher returns than low BE/ME stocks– exhibits an irregular pattern, which is consistent with the results of recent literature on market anomalies on international equity markets. Specifically, using Japanese stocks, Daniel et al. (2001) find a significant value premium for the largest size quintile stocks, where high BE/ME stocks beat low BE/ME stocks by 0.994% per moth. However, the authors find an insignificant value premium in small stocks. Similar results are provided by Fama and French (2012) using a sample of 23 developed stock markets divided into 4 regional areas, where the authors document higher value premia in Japan for largest size quintile stocks. By contrast, Fama and French (2006) find that, in the US market, significant value premia –return differences between the top-2 and the bottom-2 BE/ME quintiles– exist for all size groups, except the largest-cap group. However, for merged data from 14 non-US developed national markets, the authors find that the value premium is almost equal for most size groups.

Panel B in Table 1 shows mean returns and standard deviations for 20 momentum portfolios. As shown, momentum portfolios

Table 1
Summary statistics.

Panel A: 25 size-BE/ME portfolios										
Size	Low	2	3	4	High	Low	2	3	4	High
	Means					St. Dev.				
Small	2.97	2.51	2.91	1.81	1.90	12.39	8.80	8.81	6.88	6.27
2	1.59	1.65	1.47	1.26	1.57	9.75	7.53	7.11	6.34	6.19
3	0.92	1.03	1.06	1.07	1.62	8.91	7.09	6.55	6.16	6.56
4	0.65	0.97	0.93	1.03	1.18	7.82	6.62	6.05	5.99	6.50
Big	0.35	0.63	1.00	0.95	0.93	6.32	5.83	5.65	5.91	7.25
Panel B: 20 momentum portfolios										
	1	2	3	4	5	1	2	3	4	5
	Means					St. Dev.				
Low-5	−2.09	−0.96	−0.53	−0.19	−0.06	10.72	8.65	7.80	7.48	7.08
6–10	0.05	0.20	0.41	0.61	0.66	6.86	6.97	6.97	7.04	6.63
11–15	0.67	0.73	1.10	1.06	1.38	6.62	6.18	6.44	6.41	6.22
16-High	1.53	1.86	2.16	2.81	4.30	6.14	6.44	6.63	7.67	9.43
Panel C: 61 industry portfolio deciles										
	1	2	3	4	5	6	7	8	9	10
Means	0.53	0.61	0.67	0.68	0.71	0.75	0.79	0.83	0.89	1.31
St. Dev.	5.81	6.13	6.25	6.68	6.96	7.25	7.81	8.63	9.20	20.03
Panel D: Macroeconomic series										
	Means					St. Dev.				
	ΔC	RF	ΔT	ΔRD		ΔC	RF	ΔT	ΔRD	
	1.41	1.26	3.04	2.69		1.58	1.64	10.10	4.40	

Notes: We compile monthly series from the Datastream database for all stocks traded on the Japanese equity market, from January 1983 to December 2019. In order to estimate excess returns, we use the three-month Treasury Bill rate for Japan. Additionally, we compile total consumption of households series, exports and imports of goods and services, and R&D investment from the OECD database. All results are monthly percentages, except those for macroeconomic data series, which are annual percentages.

report a significant spread between past winners and past losers, which contrasts with the results achieved by Fama and French (2012), who find that the momentum effect is negligible for Japan. Furthermore, Asness et al. (2013) find that the momentum effect in the Japanese equity market is much weaker than in other countries. However, unlike these studies, we create momentum portfolios rebalancing the portfolio components and weights once a year instead of monthly, which explains our results. Remarkably, when we rebalance the portfolios on a monthly basis the momentum effect disappears (not shown in Table 1), consistently with the studies referred above.

Panel C in Table 1 shows the deciles of the average and standard deviation of the excess returns of 61 industry portfolios. As usual in this sort of portfolios, the expected returns do not exhibit a clear pattern and their variability across industries is relatively low. Regarding correlations, Table 2 shows that while portfolio returns are positively correlated with consumption growth, both ΔT and ΔRD exhibit a weaker correlation, yielding positive or negative results depending on the specific portfolio. However, it should be noted that, according to expression (6), the performance of the models under analysis does not depend on these correlations, but on the correlation of expected returns with the covariance between expected returns and model factors, as shown in the following section.

5. Results and discussion

Table 3 shows the regression results for all the models under consideration, on an annual basis. Depending on the specific model and its unconditional or conditional nature, we use the required vector of factors from expressions (8) and (11), respectively. More specifically, model 1 in Table 3 shows the results provided by the unconditional CCAPM, while models 2 and 3 comprise the results delivered by the Constatinides-Duffie model using ΔT and ΔRD as proxies for idiosyncratic risk, respectively. Models 4 and 5 show the

Table 2
Correlations.

Panel A: 25 size-BE/ME portfolios										
Size	Low	2	3	4	High	Low	2	3	4	High
			ΔC					RF		
Small	0.14	0.14	0.20	0.15	0.21	−0.28	−0.27	−0.22	−0.22	−0.14
2	0.07	0.14	0.12	0.24	0.27	−0.32	−0.27	−0.20	−0.17	−0.10
3	0.11	0.13	0.11	0.27	0.26	−0.26	−0.22	−0.23	−0.17	−0.13
4	0.07	0.16	0.23	0.28	0.23	−0.26	−0.21	−0.18	−0.13	−0.13
Big	0.16	0.20	0.29	0.28	0.21	−0.18	−0.09	−0.10	−0.14	−0.08
			ΔT					ΔRD		
Small	0.12	0.14	0.10	−0.01	0.01	0.04	0.02	0.13	−0.02	0.11
2	0.09	0.09	−0.16	0.03	0.03	−0.04	0.01	−0.04	0.07	0.13
3	0.07	−0.01	−0.01	0.05	−0.03	0.02	0.00	0.00	0.11	0.09
4	−0.08	0.03	−0.01	−0.01	−0.03	−0.07	0.06	0.11	0.11	0.09
Big	−0.15	−0.26	−0.11	−0.05	−0.09	0.02	0.05	0.12	0.07	0.05
Panel B: 20 momentum portfolios										
	1	2	3	4	5	1	2	3	4	5
			ΔC					RF		
Low-5	0.15	0.21	0.23	0.24	0.31	−0.06	−0.13	−0.06	−0.03	−0.06
6–10	0.24	0.35	0.29	0.35	0.40	−0.03	−0.02	−0.04	−0.01	0.14
11–15	0.34	0.22	0.26	0.27	0.23	−0.01	−0.12	−0.09	−0.11	−0.12
16-High	0.23	0.29	0.21	0.09	0.02	−0.12	−0.03	−0.11	−0.15	−0.18
			ΔT					ΔRD		
Low-5	−0.28	−0.18	−0.23	−0.19	−0.13	−0.03	0.03	−0.01	0.09	0.10
6–10	−0.10	−0.03	−0.16	−0.01	−0.11	0.10	0.20	0.12	0.20	0.26
11–15	0.01	0.04	0.01	0.03	0.07	0.26	0.20	0.20	0.21	0.22
16-High	−0.02	−0.07	−0.01	0.03	−0.08	0.16	0.25	0.19	0.17	−0.06
Panel C: 61 industry portfolio deciles										
			ΔC					RF		
1–5	0.05	0.10	0.13	0.18	0.21	−0.22	−0.18	−0.15	−0.13	−0.12
6–10	0.22	0.25	0.26	0.27	0.34	−0.10	−0.08	−0.06	−0.02	0.06
Deciles			ΔT					ΔRD		
1–5	−0.22	−0.16	−0.13	−0.10	−0.07	−0.09	−0.03	0.02	0.05	0.07
6–10	−0.04	−0.02	0.03	0.05	0.21	0.11	0.13	0.17	0.19	0.31

Notes: We compile monthly series from the Datastream database for all stocks traded on the Japanese equity market, from January 1983 to December 2019. In order to estimate excess returns, we use the three-month Treasury Bill rate for Japan. Additionally, we compile total consumption of households series, exports and imports of goods and services, and R&D investment from the OECD database. We use annual series to estimate correlations.

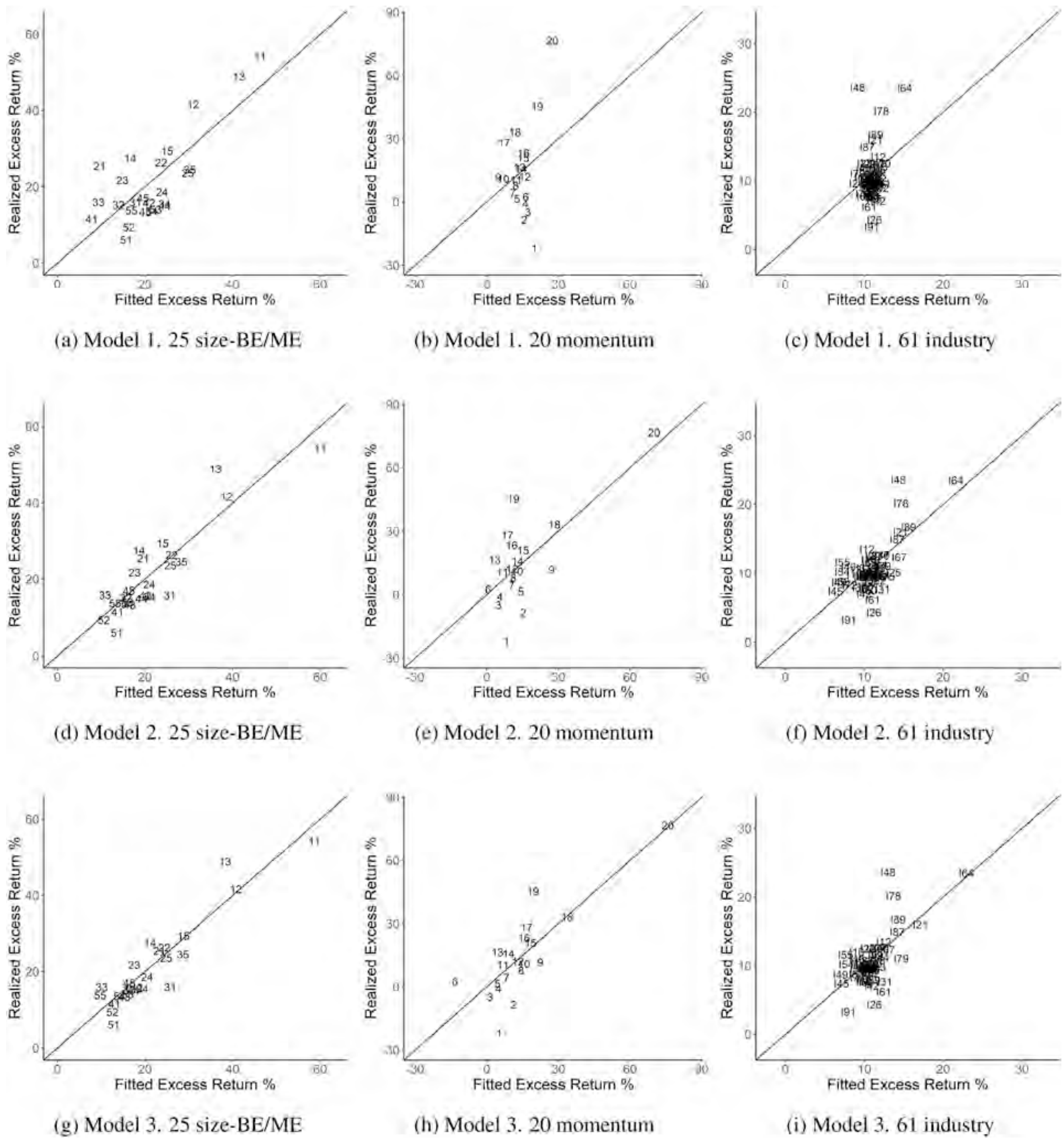
Table 3
Cross-sectional regression results using ΔT and ΔRD as explanatory variables

		Model 1	Model 2–3		Model 4–5				R^2	MAE(%)	$J-test$
	Intercept	$\lambda(\Delta C_{t+1})$	$\lambda(\Delta T_{t+1})$	$\lambda(\Delta RD_{t+1})$	$\lambda(\Delta T_t)$	$\lambda(\Delta T_t \Delta C_{t+1})$	$\lambda(\Delta RD_t)$	$\lambda(\Delta RD_t \Delta C_{t+1})$			
Panel A: 25 size-BE/ME portfolios											
1	−0.056	0.058							0.592	6.61	23.229
	(−0.339)	(1.228)							0.369		(0.447)
	(−0.069)	(0.496)									
2	−0.135	0.043	0.144						0.804	4.05	34.501
	(−0.800)	(1.838)	(1.147)						0.730		(0.044)
	(−0.166)	(0.314)	(0.414)								
3	−0.192	0.041		0.115					0.863	3.30	34.661
	(−0.945)	(1.669)		(1.532)					0.522		(0.042)
	(−0.182)	(0.356)		(0.341)							
4	0.017	0.042			0.175	0.003			0.769	4.77	33.297
	(0.100)	(1.851)			(0.998)	(1.013)			0.031		(0.043)
	(0.016)	(0.385)			(0.194)	(0.723)			.		
5	−0.158	0.061					0.044	0.002	0.708	4.94	13.061
	(−0.776)	(1.233)					(0.595)	(1.087)	0.519		(0.906)
	(−0.222)	(0.474)					(0.075)	(0.180)			
Panel B: 20 momentum portfolios											
1	0.293	−0.034							0.059	15.04	86.201
	(1.246)	(−1.029)							−0.078		(0.000)
	(0.169)	(−0.086)									
2	−0.513	0.049	0.376						0.483	11.37	23.461
	(−1.567)	(1.614)	(1.481)						−0.319		(0.135)
	(−0.186)	(0.143)	(0.302)								
3	−0.593	0.041		0.178					0.655	9.22	21.027
	(−1.643)	(1.260)		(1.795)					−0.192		(0.225)
	(−0.374)	(0.161)		(0.306)							
4	0.242	−0.023			0.051	−0.006			0.885	5.44	20.257
	(0.724)	(−0.484)			(0.274)	(−1.181)			0.507		(0.209)
	(0.398)	(−0.192)			(0.090)	(−0.673)					
5	0.217	−0.018					−0.001	−0.004	0.818	6.89	11.312
	(0.483)	(−0.314)					(−0.010)	(−0.831)	0.388		(0.790)
	(0.177)	(−0.113)					(−0.003)	(−0.297)			
Panel C: 61 industry portfolios											
1	0.086	0.004							0.067	2.25	47.076
	(1.606)	(0.495)							0.057		(0.868)
	(0.426)	(0.072)									
2	0.040	0.003	0.042						0.461	1.94	38.544
	(0.882)	(0.370)	(1.296)						−0.009		(0.997)
	(0.160)	(0.079)	(0.403)								
3	0.024	0.000		0.014					0.445	1.76	26.596
	(0.458)	(0.024)		(0.878)					0.239		(1.000)
	(0.091)	(0.005)		(0.302)							
4	0.076	0.005			−0.017	0.001			0.374	1.98	37.137
	(1.417)	(0.604)			(−0.354)	(0.822)			0.348		(0.981)
	(0.433)	(0.131)			(−0.064)	(0.265)					
5	0.086	0.003					−0.001	0.000	0.239	2.11	39.408
	(1.657)	(0.434)					(−0.033)	(0.460)	0.177		(0.963)
	(0.501)	(0.073)					(−0.005)	(0.083)			

The table displays three rows for each model, where the first row shows the coefficient estimates, the second row the t-statistics estimated by GMM, and the third row the t-statistics determined using the methodology suggested by Kan et al. (2013). OLS and GLS R^2 statistics are provided for each model, in that order.

results provided by the conditional CCAPM using ΔT and ΔRD as instruments, respectively. These conditional models use a lag number of one year for ΔT and ΔRD in expression (10).

We use the generalized method of moments (GMM) to simultaneously estimate all betas and lambdas in expressions (7) and (10) in order to replicate the two-pass cross-sectional regression (CSR) procedure, correcting standard errors for cross-sectional autocorrelation and for the fact that betas are estimated regressors. Specifically, following Cochrane (2005) (pp. 241–243), we use the following moment restrictions:



(a) Model 1. 25 size-BE/ME (b) Model 1. 20 momentum (c) Model 1. 61 industry

(d) Model 2. 25 size-BE/ME (e) Model 2. 20 momentum (f) Model 2. 61 industry

(g) Model 3. 25 size-BE/ME (h) Model 3. 20 momentum (i) Model 3. 61 industry

Fig. 1. Realized excess returns versus fitted values.
Notes: We depict 25 size-BE/ME portfolios according to a code with two numbers, the first number being the size code (with 1 being the smallest and 5 the largest) and the second number being the BE/ME ratio code (with 1 representing a low ratio and 5 a high ratio). Momentum portfolios are represented by a number ranging from 1 to 20, where 1 denotes the portfolio comprising the past loser stocks and 20 denotes the portfolio comprising the past winners. We depict industry portfolios according to the letter ‘I’ followed by the first two digits of the SIC code.

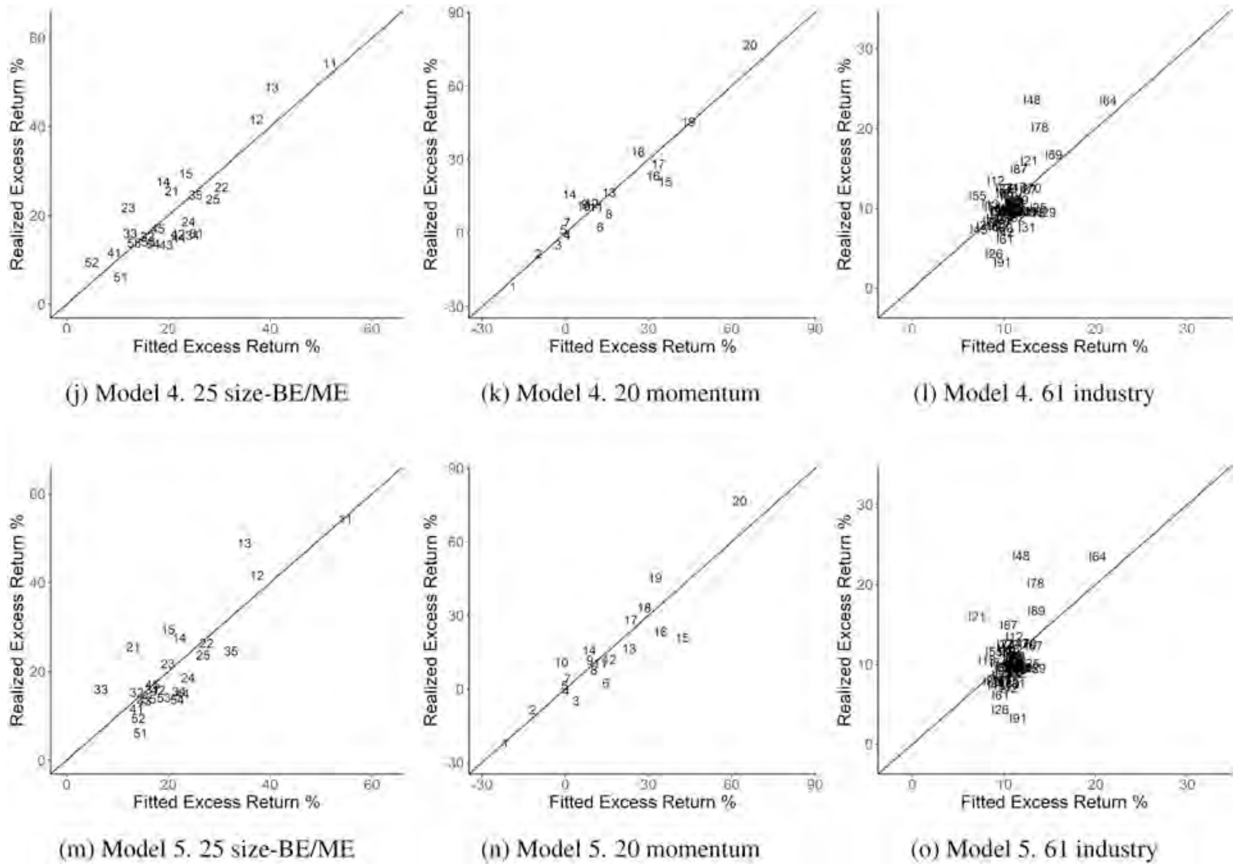


Fig. 1. (*continued*).

$$\mathbf{g_T}(\mathbf{b}) = \left\{ \begin{array}{c} \mathbf{E}\left(\mathbf{R}_t^e - \mathbf{a} - \boldsymbol{\beta}\mathbf{X}_t\right) = 0 \\ \mathbf{E}\left[\left(\mathbf{R}_t^e - \mathbf{a} - \boldsymbol{\beta}\mathbf{X}_t\right)\mathbf{X}_t\right] = 0 \\ \mathbf{E}\left(\mathbf{R}_t^e - \boldsymbol{\beta}\boldsymbol{\lambda}\right) = 0 \end{array} \right\} \tag{12}$$

where $\mathbf{a}$, $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are parameters and $\mathbf{X_t}$ is the vector of explanatory variables. For each model, Table 3 provides three rows, where the first row shows the coefficient estimates, the second row the *t*-statistics estimated by GMM, and the third row the *t*-statistics determined using the methodology suggested by Kan et al. (2013). Importantly, Kan et al. (2013) explain that model misspecification can lead to important distortions in the standard errors of model coefficients. Furthermore, the authors provide general expressions for the asymptotic variance of model coefficients under potential model misspecification. Hence, for each model in Table 3, the third row uses the Kan et al. (2013) correction to evaluate the effect of model misspecification on the statistical significance of model coefficients.

Following Lewellen et al. (2010), Table 3 also reports both ordinary least squares (OLS) and generalized least squares (GLS) R^2 statistics, in that order, for each model. Additionally, Table 3 shows the mean absolute error (MAE) and the results provided by the *J*-test for overidentifying restrictions.

As shown in Table 3, in general, the classic CCAPM (model 1) performs acceptably for size-BE/ME portfolios in Panel A, while it performs significantly worse for momentum and industry portfolios. Conversely, ΔT and ΔRD are highly explanatory for all portfolios under consideration when they are used as additional factors into the CCAPM (models 2 and 3) or as instruments (models 4 and 5). In particular, while Panel A in Table 3 shows that the unconditional CCAPM provides an OLS R^2 statistic of 59.2% and a MAE of 6.61% for size-BE/ME portfolios, the performance of the model improves substantially when we include ΔT or ΔRD as additional explanatory variables. Hence, the Constantinides-Duffie model provides an OLS R^2 statistic and a MAE of 80.4% and 4.05%, respectively, when we proxy idiosyncratic risk by ΔT (model 2), while this indicator performs slightly worse when used as an instrument in model 4, providing an OLS R^2 statistic and a MAE of 76.9% and 4.77%, respectively. Analogously, Panel A in Table 3 shows that ΔRD is specially informative when used as a factor (model 3), allowing the Constantinides-Duffie model to provide an OLS R^2 statistic of 86.3% and a MAE equal to 3.3%. Nevertheless, the last column in Table 3 shows that the *J*-test for overidentifying restrictions rejects most of the models in Panel A, with the exception of models 1 and 5.

Fig. 1 allows us to better understand the relationship between the expected excess returns in the data and the fitted values provided by the models shown in Table 3. Specifically, Fig. 1 plots the realized values and the fitted values provided by the models under consideration, showing that, especially for models 2–4, the fitted values obtained for size-BE/ME portfolios are close to their observed counterparts. This suggests that the fact that the *J*-test for overidentifying restrictions rejects models 2–4 in Table 3, Panel A, is mainly due to the low variability of pricing errors across portfolios, rather than their high absolute value.

Panel B in Table 3 shows that momentum portfolios constitute a more stringent hurdle for the CCAPM than size-BE/ME portfolios. In fact, in that case, the CCAPM provides an OLS R^2 statistic of 5.9%, while its MAE amounts to 15.04%. Importantly, both ΔT and ΔRD help to significantly improve the performance of the model either when these variables enter the pricing function as additional factors (models 2 and 3) or as instruments (models 4 and 5). Indeed, our results show that ΔT allows the conditional CCAPM (model 4) to reach an OLS R^2 statistic of 88.5% and reduce the MAE to 5.44%. It is worth noting that, although the explanatory power of ΔT persists when it is used as a factor in model 2, it performs more modestly, delivering an OLS R^2 statistic and a MAE of 48.3% and 11.37%, respectively.

The results in Table 3, Panel B, show that ΔRD performs well when used as a proxy for idiosyncratic risk in the Constantinides-Duffie model (model 3), but especially when used to scale consumption betas in model 5. Specifically, the Constantinides-Duffie model provides a lower OLS R^2 statistic (65.5%) and a higher MAE (9.22%) than the conditional CCAPM, which provides an OLS R^2 statistic and a MAE of 81.8% and 6.89%, respectively. In this regard, Fig. 1 shows that momentum portfolios produce more scattered fitted values when ΔT and ΔRD are used as factors in models 2 and 3 than when used as instruments in models 4 and 5. This is consistent with the fact that the GLS R^2 statistics of models 2 and 3 are extremely low, meaning that their factor mimicking portfolios are far from being mean-variance efficient (Lewellen et al., 2010). In any case, it should be noted that the *J*-test for overidentifying restrictions does not reject models 2–5 in Panel B.

Regarding industry portfolios, Panel C in Table 3 shows that, as in the case of the momentum portfolios, ΔT and ΔRD clearly contribute to improving the performance of the classic CCAPM, although these variables exhibit a lower explanatory in Panel C than Panels A and B, in part due to the small variability of expected returns across industries. Indeed, industry portfolios have traditionally been a major hurdle for most asset pricing models, as their expected returns are often poorly correlated with the vast majority of factor betas (Fama and French, 1997). More specifically, the results in Table 3, Panel C, show that both ΔT and ΔRD perform better when used as factors in the Constantinides-Duffie model (models 2 and 3) than when used as instruments in the conditional CCAPM (models 4 and 5). Thus, while the classic CCAPM provides an OLS R^2 statistic and a MAE of 6.7% and 2.25%, respectively, ΔT allows the Constantinides-Duffie model to reach an OLS R^2 statistic of 46.1% and a MAE of 1.94%. Analogously, ΔRD leads the Constantinides-Duffie model to provide an OLS R^2 statistic and a MAE of 44.5% and 1.76%, respectively. The results in Panel C for models 4 and 5 show that, although ΔT and ΔRD also help improve the performance of the conditional CCAPM relative to its unconditional counterpart, their performance is more modest, delivering OLS R^2 statistics equal to 37.4% and 23.9%, respectively. Remarkably, the *J*-test for overidentifying restrictions does not reject any model in Panel C, mainly due to the small size of pricing errors relative to their dispersion across portfolios (see Fig. 1).

It should be mentioned that, despite the economical significance of ΔT and ΔRD in estimating the expected returns of the portfolios under analysis, in all cases the lambda coefficients are not statistically significant, meaning that their value may be subject to strong

Table 4
Cross-sectional regression results using the IK ratio and the CCI as instruments.

–	Models a-b						R^2	MAE(%)	$J-$ test
	Intercept	$\lambda(\Delta C_{t+1})$	$\lambda(IK_t)$	$\lambda(IK_t\Delta C_{t+1})$	$\lambda(CCI_t)$	$\lambda(CCI_t\Delta C_{t+1})$			
Panel A: 25 size-BE/ME portfolios									
a	−0.069	0.018	−0.003	0.000			0.910	2.98	51.165
	(−0.787)	(1.148)	(−0.107)	(0.612)			0.313		(0.000)
	(−0.223)	(0.257)	(−0.031)	(0.154)					
b	−0.079	0.035			0.713	0.015	0.851	3.57	38.363
	(−0.657)	(2.032)			(0.468)	(0.349)	0.827		(0.012)
	(−0.157)	(0.492)			(0.139)	(0.096)			
Panel B: 20 momentum portfolios									
a	−0.148	−0.024	−0.090	0.003			0.684	8.86	11.406
	(−0.554)	(−0.318)	(−0.700)	(−0.991)			0.126		(0.784)
	(−0.039)	(−0.154)	(−0.180)	(−0.304)					
b	0.487	−0.039			1.599	−0.110	0.729	8.85	10.535
	(0.767)	(−0.518)			(0.456)	(−0.736)	0.304		(0.837)
	(0.225)	(−0.150)			(0.134)	(−0.321)			
Panel C: 61 industry portfolios									
a	0.060	0.002	−0.004	0.000			0.157	2.21	41.262
	(1.257)	(0.269)	(−0.308)	(−0.112)			−0.204		(0.942)
	(0.335)	(0.040)	(−0.069)	(−0.023)					
b	0.063	0.004			−0.214	0.004	0.328	2.07	39.718
	(1.336)	(0.728)			(−0.338)	(0.271)	0.120		(0.960)
	(0.371)	(0.118)			(−0.056)	(0.062)			

Notes: The table displays three rows for each model, where the first row shows the coefficient estimates, the second row the *t*-statistics estimated by GMM, and the third row the *t*-statistics determined using the methodology suggested by Kan et al. (2013). OLS and GLS R^2 statistics are provided for each model, in that order.

sampling variation. Although this lack of significance is usual in macroeconomic asset pricing models (Lettau and Ludvigson, 2001; Lustig and Van Nieuwerburgh, 2005; Parker and Julliard, 2005), primarily due to measurement errors tied to macroeconomic series, the comparison between the *t*-statistics provided by GMM and those determined following the Kan et al. (2013) methodology shows that model misspecification translates into significantly higher standard errors and, consequently, lower *t*-statistics. According to Kan et al. (2013), this is often the case with macroeconomic asset pricing models, where the low correlation between asset returns and factors leads to an important impact of misspecification on the asymptotic variance of lambda coefficients.

Additionally, in order to compare the performance of the models shown in Table 3 with that of the conditional CCAPM scaled by other instruments well-documented in the literature, Table 4 shows the regression results delivered by the conditional CCAPM using two additional instruments, namely: (i) the investment-capital ratio (hereafter, IK ratio), determined using the Cochrane (1991) methodology on Japanese gross capital formation data series, as provided by the OECD, and (ii) the consumer confidence index (hereafter, CCI) for Japan in the period under study (dataset 'Composite Leading Indicators' MEI, from the OECD Statistics Section). Importantly, while Cochrane (1991) shows that the IK ratio exhibits significant predictive power in forecasting stock returns, Ludvigson (2004) and Sommer (2007) emphasize the good performance of the CCI in forecasting consumption growth due its strong relationship with habit formation.

The results in Table 4 show that although the IK ratio and the CCI do a good job when used as instruments in the conditional CCAPM (models a and b in Table 4, respectively), in general they do not allow the model to outperform models 2–5 in Table 3. In particular, for size-BE/ME portfolios in Table 4 Panel A, the IK ratio and the CCI provide OLS R^2 statistics of 91% and 85.1%, respectively, while their

Table 5
Test of equality of cross-sectional R^2 statistics.

	Model 2	Model 3	Model 4	Model 5	Model a	Model b
Panel A: 25 size-BE/ME portfolios						
Model 1	−0.212	−0.271	−0.177	−0.116	−0.318	−0.258
	(0.632)	(0.579)	(0.659)	(0.671)	(0.555)	(0.613)
Model 2		−0.059	0.035	0.097	−0.106	−0.046
		(0.421)	(0.795)	(0.782)	(0.483)	(0.682)
Model 3			0.094	0.155	−0.047	0.012
			(0.541)	(0.695)	(0.662)	(0.909)
Model 4				0.062	−0.140	−0.081
				(0.867)	(0.477)	(0.679)
Model 5					−0.202	−0.143
					(0.657)	(0.725)
Model a						0.059
						(0.551)
Panel B: 20 momentum portfolios						
Model 1	−0.424	−0.596	−0.827	−0.759	−0.625	−0.670
	(0.766)	(0.650)	(0.434)	(0.514)	(0.564)	(0.597)
Model 2		−0.172	−0.403	−0.335	−0.201	0.246
		(0.752)	(0.618)	(0.722)	(0.820)	(0.837)
Model 3			−0.231	−0.163	−0.029	−0.074
			(0.631)	(0.793)	(0.971)	(0.937)
Model 4				0.068	0.201	0.156
				(0.840)	(0.760)	(0.832)
Model 5					0.134	0.089
					(0.835)	(0.877)
Model a						−0.045
						(0.959)
Panel C: 61 industry portfolios						
Model 1	−0.394	−0.379	−0.307	−0.172	−0.090	−0.262
	(0.000)	(0.000)	(0.000)	(0.038)	(0.056)	(0.003)
Model 2		0.016	0.087	0.222	0.304	0.133
		(0.715)	(0.136)	(0.011)	(0.001)	(0.049)
Model 3			0.071	0.206	0.288	0.117
			(0.139)	(0.021)	(0.000)	(0.128)
Model 4				0.135	0.217	0.046
				(0.021)	(0.000)	(0.404)
Model 5					0.082	−0.089
					(0.197)	(0.005)
Model a						−0.171
						(0.010)

Notes: The table shows the results of pairwise test of equality of the OLS R^2 statistics for the following models: (i) the unconditional CCAPM (model 1), (ii) the Constantinides-Duffie model using ΔT as a proxy for idiosyncratic risk (model 2), (iii) the Constantinides-Duffie model using ΔRD as a proxy for idiosyncratic risk (model 3), (iv) the conditional CCAPM scaled by ΔT (model 4), (v) the conditional CCAPM scaled by ΔRD (model 5), (vi) the conditional CCAPM scaled by the IK ratio (model a), and (vii) the conditional CCAPM scaled by the CCI (model b). We report the difference between the sample cross-sectional OLS R^2 statistics of the models in row *i* and column *j*, $R_i^2 - R_j^2$, and the associated *p*-values (in parentheses) under the null of equality of R^2 statistics.

MAEs amount to 2.98% and 3.57%, thus slightly outperforming models 2–5 in Table 3 Panel A. However, for momentum portfolios, Tables 3 and 4 show that, while the IK ratio and the CCI provide better results than ΔT and ΔRD when these variables are used as factors in models 2 and 3, the opposite is true when ΔT and ΔRD are used as instruments in models 4 an 5. Furthermore, in the case of industry portfolios, in most cases ΔT and ΔRD allow models 2–5 in Table 3 to outperform models a and b in Table 4, helping both the Constantinides-Duffie model and the conditional CCAPM to generally provide higher R^2 statistics and lower MAEs than the IK ratio and the CCI.

Despite the high explanatory power of both the Constantinides-Duffie model and the conditional CCAPM scaled by ΔT and ΔRD in explaining the expected returns of the portfolios under study, it should be noted that the problems arising from model misspecification, measurement errors in the explanatory variables or sampling variation hinder a direct comparison of the models simply by observing their R^2 statistics, MAEs or the p-value provided by the J-test for overidentifying restrictions. In this regard, Kan et al. (2013) develop a test of model comparison based on the sample cross-sectional R^2 statistic, that allows the authors to straightforwardly compare two competing beta models. Therefore, considering that in our study the Constantinides-Duffie model and the conditional CCAPM nest the classic CCAPM, Table 5 reports the pairwise tests of equality of the OLS R^2 statistics for all models under study, where p-values are shown in parentheses.

In general, the results in Table 5 do not allow us to reject the null of equality of OLS R^2 statistics except for industry portfolios (Panel C). In that case, models 2–5 and model b clearly dominate the classic CCAPM, while models 2–4 also dominate the conditional CCAPM scaled by the IK ratio (model a). Furthermore, the differences in the R^2 statistics of models 2 and 5 with that of the conditional CCAPM scaled by the CCI (model b) are also statistically significant. These results are consistent with those obtained by Kan et al. (2013), who find differences in R^2 statistics up to 65% that are still not statistically significant. Thus, although the results in Table 5 complement those shown in Tables 3 and 4 for the models under study, also highlight that model misspecificacion, measurement errors and sampling variation in economic series seriously hinder model comparison in practice.

In sum, our results suggest that income inequality, as measured by ΔT and ΔRD, considerably help the classic CCAPM to improve its performance on the Japanese equity market. Thus, following the OECD (2011) and Dabla-Norris et al. (2015), the significant impact of trade openness and technological progress on income inequality seems to make ΔT and ΔRD good candidates to capture pricing information not included in consumption growth. This fact is consistent with idiosyncratic risks that are not perfectly insured due to market incompleteness and nonlinear investor preferences, but also with the possibility that income inequality constitutes an important piece of the conditioning information used by investors in making their economic decisions. Nevertheless, the results shown in Table 3 and Fig. 1 show that the effect of income inequality on model performance varies significantly across portfolios, which suggests that additional variables other than consumption growth and income inequality strongly determine the behavior of stock returns.

6. Conclusions

Although consumption-based asset pricing, as pioneered by Lucas (1978), constitutes a solid body of work that allows us to explicitly relate asset pricing and macroeconomics, most empirical tests on perfect risk-sharing tend to reject it, which puts into question the representative investor approach, typically assumed by consumption models. In this framework, the Constantinides-Duffie model constitutes a powerful approach for the task of analyzing the asset pricing implications of untraded risks. In any case, the difficulties in correctly estimating idiosyncratic risk and, more precisely, the cross-sectional variance of consumption growth, seriously hinders the use of this methodology for practical purposes. In this context, our approach exploits the tight relationship of income inequality with market openness and R&D investment, as explained in Milanovic and Squire (2005), Papageorgiou et al. (2008), Harrison et al. (2010), OECD (2011) and Dabla-Norris et al. (2015), to proxy the cross-sectional variance of consumption growth by trade openness, defined as the growth rate of exports plus imports, and the growth of national R&D expense. Furthermore, we analyze the explanatory power of ΔT and ΔRD when used as a part of the information sets of investors in making their economic decisions.

Our results show that both ΔT and ΔRD contribute significantly to improve the results provided by the classic consumption-based asset pricing model. In particular, both variables perform satisfactorily when they are used either as additional explanatory variables within the Constantinides-Duffie setup, or as instruments to parameterize the SDF of the conditional CCAPM. However, depending on the specific class of portfolio, the models under study provide mixed results. Thus, while both ΔT and ΔRD work better when used as a proxy for idiosyncratic risk in the case of size-BE/ME portfolios and industry portfolios, these indicators perform better when used as instruments in the case of momentum portfolios.

In the light of these results, further research on the role of trade openness and R&D investment in asset pricing is mandatory. First, future research should examine the prevalence of our results in other countries with well-differentiated patterns in consumption growth. In this regard, Rojo-Suárez et al., 2021 show that disparities in consumption patterns across countries can substantially affect the performance of consumption-based asset pricing models. This fact can lead to substantial differences in the effect of income inequality on stock returns.

Second, the influence of idiosyncratic risk on asset returns is directly determined by market incompleteness, which is a common feature of financial markets worldwide. In this regard, future research should provide further insight on the relationship of the explanatory power of trade openness and R&D investment on asset prices with country-level risk-sharing. For that purpose, our approach can be largely complemented with those followed by Cochrane (1991), Ogaki and Zhang (2001), Kim et al. (2006) and Broner and Ventura (2011) in order to analyze the role of idiosyncratic taste shocks and the effect of globalization on risk-sharing.

Finally, throughout the paper we assume that investors are aware of the true model driving their economic decisions, as usual in a large part of the asset pricing literature. However, following Hansen and Sargent (2008), Epstein and Schneider (2010) and Strzalecki (2011), the literature on ambiguity aversion argues that investors usually behave conservatively with respect to ambiguity, acting as if the 'worst-reasonable-case' model is true. Moreover, unexpected shocks on trade openness and R&D investment can have important implications on asset prices, which are unexplored in this paper, but can be satisfactorily addressed complementing our perspective with that followed by macroeconomic learning models, as those suggested by Pastor and Veronesi (2009) and Johannes et al. (2016).

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