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Predicting risk premium under changes in the conditional distribution of stock returns[☆]

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ABSTRACT

The goal of this paper is to assess time-variation in asset returns while considering the whole conditional distribution. We use a quantile regression framework and quarterly data for the U.S., and show that the probabilistic distribution of expectations about future stock returns changes in response to variation in commonly used explanatory variables. Moreover, our results support the idea that lower quantiles are less stable than upper quantiles, thus, suggesting that asset pricing models are particularly accurate in capturing the expectations that less risk-averse agents have about future returns.

1. Introduction

Fluctuations in risk are important to explain consumption and investment behaviour and, therefore, business cycle patterns. Similarly, periods of booms and busts in asset prices are generally associated with variation in expectations that agents have about future risk premium. By analyzing these movements, it may be possible to detect earlier manifestations of asset misalignments and take corrective measures. Therefore, understanding the determinants of risk, elusive a goal as it may be, is crucial for policies aiming at macro-financial stability.

While the empirical finance literature has shown that expected excess returns on assets tend to be counter-cyclical[1] and numerous economically motivated variables capture time-variation in risk premium,[2] another line of investigation has considered that the mean and variance are not necessarily sufficient for risk averse investors to base their portfolio decisions on. Other characteristics of the distribution of returns such as skewness (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000) or even kurtosis or higher moments (Scott and Horvath, 1980) of stock returns should also matter.

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[1] See Fama (1970, 1991, 1998), Fama and French (1996), Campbell and Cochrane (1999) and Duffee (2005).

[2] See, for instance, Lettau and Ludvigson (2001), Lustig and Van Nieuwerburgh (2005), Parker and Julliard (2005), Yogo (2006), Piazzesi et al. (2007), Campbell and Diebold (2009) and Sousa (2010, 2015a).

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In this paper, we look at the evolution of the distribution of risk premium over time and, as a by-product, at the issue of deviations of an asset from its "fundamental value", i.e. the one provided by a specific asset pricing model. These deviations can be indicative of under or over valuation of the asset and can signal important mispricing in the market. However, a major difficulty arises when determining what a "large" deviation from fundamentals is due to the lack of a clear criterion.

In this context, our paper retakes a technique that has been widely used in economics and empirical finance.[3] More specifically, we use quantile regressions to estimate the probability distribution of asset returns and to investigate the extent to which changes in expectations about risk premium help detecting periods of "abnormal" returns. The main advantage of this econometric framework is that it allows us to condition the whole distribution of asset returns on a set of explanatory variables, that is, we can estimate not only the median but also any quantile of the distribution of asset returns. In addition, extreme events characterizing the tails of the distribution of asset returns and situations of large outliers can be identified and predicted without resorting on "ad hoc" definitions (Koenker and Hallock, 2001). Thus, quantile regressions, as ways of characterizing and predicting the distribution of returns, can be valuable for asset pricing and a benchmark for detecting asset price misalignments, providing an analysis that is more robust than the ordinary least squares (OLS) regression that focuses only on the mean.

We start with an agnostic approach, trying to link asset returns with a series of explanatory variables in a way that is not fully grounded on equilibrium models derived from theory. In a second stage, we analyze the results of a large set of asset pricing models.

Using data for the US, we show that the probabilistic distribution of stock returns is time-varying. Moreover, we find that several macroeconomic and financial variables help explaining such variation. The results of the forecasting regressions are consistent with theoretical predictions and so monitoring these factors can help assessing attitudes towards risk. In particular, we find evidence that credit growth and long-term consumption growth predict a fall in future stock returns, which suggests more appetite for risk-taking.

With regard to the results based on asset pricing models, we conclude that there are various models that are useful in explaining time-variation in the probability distribution of returns. We show that lower quantiles tend to be less stable than upper quantiles. If the lower quantiles can be attributed to agents that are more prone towards risk while the upper quantiles depend on those that are more averse to risk, our findings highlight that asset pricing models are particularly accurate in capturing the expectations that less risk-averse agents have about future returns.

By linking the conditional return distribution to different pricing factors, our methodology suggests that some predictors are better at picking up episodes of extremely high (low) stock returns and not just mean returns. Thus, it can help policymakers in designing macroprudential policies based on a battery of early warning indicators. It can also enhance our understanding of the drivers of the tails of the distribution of risk premium.

The research presented in this paper is indebted to the works that have focused on forecasting either the mean or the volatility of stock returns and, more specifically, to those that have either provided novel frameworks (Diebold and Yilmaz, 2009; Rua and Nunes, 2009) or highlighted the potential mis-specification associated with standard approaches (Baillie and DeGennaro, 1990; González-Rivera, 1998; González-Rivera, 2013; Almeida and Garcia, 2012, 2013; González-Rivera and Jiménez-Martín, 2012). It is also built on the literature that showed that accounting for the nonlinearity of the behaviour of stock markets, the uncertainty about the model governing asset prices or the distribution characterizing stock returns can help improving predictability (Baillie, 1993; Jawadi, 2009; Jawadi et al., 2009; Almeida et al., 2013; Sousa and Sousa, 2017). In particular, we rely on several asset pricing models as starting frameworks to address this specific issue. Then, we use quantile regressions to investigate whether these models are able to forecast time-variation in the distribution of asset returns.

The rest of the paper is organized as follows. Section 2 introduces the econometric framework and presents the data. Section 3 discusses the empirical results. Section 4 concludes with the main findings and policy implications.

2. Econometric framework and data

2.1. Conditional distribution of asset returns and quantile regressions

The distribution of the returns can be characterized by its different quantiles. In Machado and Sousa (2006), this technique was first applied to the level of stock prices with the aim of assessing misalignments. Moreover, while the more usual approach of the empirical finance literature uses the standard ordinary least squares (OLS) estimation and looks at stock returns rather than the level of stock prices, in this paper, we consider quantile regressions. A main advantage of this technique is that it allows relating the quantiles that summarize the distribution of asset returns with explanatory variables that convey information about risk premium. In fact, quantile regressions make it possible to construct probability intervals and

[3] For example, Taylor (1999) considers quantile regressions in the context of value at risk. Leon Li and Miu (2010) provide a bankruptcy prediction model with dynamic accounting-ratio-based and market-based information. Conley and Galenson (1998) explore wealth accumulation in several U.S. cities. Gosling et al. (2000) study the income and wealth distribution in the UK, while Bassett and Chen (2001) characterize mutual fund investment styles. Machado and Sousa (2005) assess the impact of macroeconomic fundamentals on the distribution of asset prices. Leon Li and Yen (2011) analyse the dynamic covariance risk in global stock markets, Lee and Leon Li (2012) assess the linkages between diversification and risk-adjusted performance and Leon Li and Wu (2014) evaluate the relationship among analysts' forecast dispersion and stock returns.

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to determine whether specific asset returns are unusually low or high. These, in turn, can be associated with deviations from assets' fundamentals. Consequently, this framework helps us to better understand the economic sources of return predictability and time-variation in risk. In addition, quantile regressions are able to deal with distribution asymmetries or deviations from normality.

Models of stock return predictability are typically specified as:

$$r_{t+1} = \Phi X_t + \varepsilon_{t+1} \tag{1}$$

where ΦX_t is the conditional mean of the return, X_t is a set of explanatory variables and ε_{t+1} is the error term. This is the most common forecasting equation for stock returns, and if estimated with OLS, it would provide mean estimates of the relation between the predictive content of the variables included in X_t and r_{t+1}.

In the current paper, we try to estimate the quantiles of the whole conditional distribution of stock returns. So for each quantile we have an equation for the conditional quantile of stock returns, denoted $q_\alpha(r_{t+1}|I_t)$, where I_t contains information known at time t:

$$q_\alpha(r_{t+1}|I_t) = \Phi_\alpha X_t + u_{t+1}, \quad \alpha \in (0, 1). \tag{2}$$

Therefore, this equation is more general (i.e. less restrictive) than the OLS approach, as the slope coefficients Φ_α can vary by quantiles. Thus, the model can be used to estimate a time-varying distribution of returns.

Note that if the effect of economic state variables on the return distribution arises through capturing extreme variation in risk premium, we should find the largest impact of such variables in the tails of the return distribution. As a result, economic theory would suggest that these variables have a large coefficient in the quantile regression sufficiently close to the left and right tail (very small or very large α values) and a small coefficient close to the center (the median).

Following Koenker and Bassett (1978) and Koenker and d'Orey (1987, 1994), the parameters of the quantile prediction model are estimated by replacing the standard quadratic loss function with the 'tick' loss function, i.e.

$$L_\alpha(e_{t+1}) = (\alpha - \mathbf{1}\{e_{t+1} < 0\})e_{t+1}, \tag{3}$$

where $e_{t+1} = r_{t+1} - \hat{q}_{\alpha,t}$ is the forecast error, $\hat{q}_{\alpha,t} = q_\alpha(r_{t+1}|\mathcal{F}_t)$ denotes the conditional quantile forecast computed at time t, and $1\{\cdot\}$ is the indicator function. Confidence intervals are computed based on inversion of a rank test described in Koenker (1994). The first-order condition associated with minimizing the expected value of (3) with respect to the forecast, $\hat{q}_{\alpha,t}$, is the α-quantile of the return distribution (Koenker, 2005), implying that the optimal forecast it the conditional quantile $\hat{q}_{\alpha,t} = F_\varepsilon^{-1}(\alpha)$, where F_t is the conditional distribution function of returns.

2.2. Data

We provide a summary of the data. We consider a set of indicators of macroeconomic activity and prices as well financial and macro-financial variables borrowed from the empirical finance literature and selected in accordance with data availability, namely:

- *Macroeconomic activity*: lagged consumption growth (ΔC_{t-1}); consumption growth over the last 12 quarters ($\Delta C_{t-1,t-12}$), i.e. the ultimate consumption risk, by Parker and Julliard (2005); real GDP growth (ΔY_{t-1}); and output gap (og_{t-1}), by Cooper and Priestley (2009).[4]
- *Prices*: inflation (π_{t-1}); change in inflation ($\Delta\pi_{t-1}$); change in housing prices (Δhp_{t-1}); and change in commodity prices (Δcp_{t-1}).
- *Financial indicators*: growth rate of credit ($\Delta cred_{t-1}$); growth rate of the monetary aggregate (Δm_{t-1}); lagged real stock returns (r_{t-1}); real government bond yield ($bond_{t-1}$); change in real government bond yield ($\Delta bond_{t-1}$); change in short-term interest rate (Δi_{t-1}); dividend yield ($divyld_{t-1}$); change in the real effective exchange rate (Δe_{t-1}); and the leverage ratio of brokers and dealers' institutions ($SBRDLR_{t-1}$), by Adrian et al. (2010).
- *Macro-financial variables*: consumption-wealth ratio (cay_{t-1}), by Lettau and Ludvigson (2001); housing wealth-to-income ratio (hwy_{t-1}), by Lustig and Van Nieuwerburgh (2005); ratio of the stock price index scaled by real GDP ($spgdp_{t-1}$), Rangvid (2006); labour income-consumption ratio (lc_{t-1}), by Santos and Veronesi (2006); ratio of durable to nondurable consumption (φ_{t-1}), by Yogo (2006) and Piazzesi et al. (2007); change in the consumption-wealth ratio (Δcay_{t-1}), by Julliard and Sousa (2007); consumption-(dis)aggregate wealth ratio ($cday_{t-1}$), by Sousa (2010); and asset wealth-to-income ratio (wy_{t-1}), by Sousa (2015a).

The data sources are the Flow of Funds Accounts (FoF) of the Board of Governors of the Federal Reserve System, the Bureau of Labor Statistics (BLS), the Organisation for Economic Co-Operation and Development (OECD) and the US Census.

[4] Campbell and Diebold (2009) show that expected business conditions capture time-variation in risk and, thus, depressed expected business conditions forecast higher asset returns. Moreover, the inclusion of expected business conditions in predictive return regressions typically reduces the forecasting power of conventional financial predictors.

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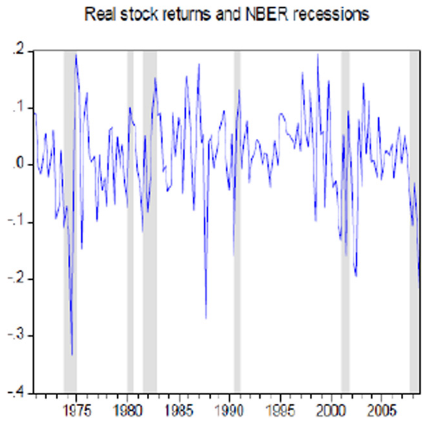

Fig. 1. Real stock returns and recession episodes.

Table 1
Forecasting real stock returns - agnostic approach: OLS regressions.

	Horizon								
	1			4			8		
Predictor	Slope	t-stat	$\bar{R}^2$	Slope	t-stat	$\bar{R}^2$	Slope	t-stat	$\bar{R}^2$
ΔC_{t-1}	−0.06	−0.03	0.00	−3.36	−0.87	0.00	−5.96	−1.08	0.00
ΔC_{t-12}	−0.31	−0.98	0.00	-1.56^{**}	−2.31	0.03	-3.52^{***}	−3.77	0.10
r_{t-1}	0.01	0.12	0.00	0.03	0.16	0.00	0.08	0.30	0.00
$bond_{t-1}$	0.16	0.53	0.00	1.58^{***}	2.49	0.04	3.31^{***}	3.67	0.09
$\Delta bond_{t-1}$	-2.88^{**}	−2.38	0.04	-4.74^{*}	−1.83	0.02	−2.17	−0.57	0.00
og_{t-1}	−0.05	−1.30	0.01	−0.10	−1.38	0.01	−0.16	−1.50	0.01
π_{t-1}	0.04	0.03	0.00	−1.21	−0.50	0.00	−0.30	−0.08	0.00
$\Delta\pi_{t-1}$	3.40	1.58	0.01	−1.08	−0.23	0.00	0.94	0.14	0.00
Δi_{t-1}	−0.01	−1.00	0.00	−0.01	0.61	0.00	−0.00	−0.19	0.00
Δm_{t-1}	−0.07	−0.08	0.00	−2.41	−1.46	0.01	-5.40^{**}	−2.30	0.03
Δhp_{t-1}	−0.30	−0.69	0.00	−1.37	−1.47	0.01	-2.34^{*}	−1.69	0.01
Δe_{t-1}	−0.00	−0.02	0.00	−0.09	−0.20	0.00	0.30	0.46	0.00
Δcp_{t-1}	−0.23	−0.52	0.00	−1.10	−1.15	0.00	−2.08	−1.51	0.01
$cday_{t-1}$	1.17^{***}	2.79	0.05	4.30^{***}	5.17	0.17	8.87^{***}	8.33	0.35
$\Delta cday_{t-1}$	0.80	1.05	0.00	1.54	0.95	0.00	0.46	0.20	0.00
cay_{t-1}	0.65	1.55	0.01	3.27^{***}	3.83	0.10	7.47^{***}	6.40	0.24
Δcay_{t-1}	0.34	0.36	0.00	−1.17	−0.58	0.00	−1.68	−0.58	0.00
lc_{t-1}	−0.02	−0.14	0.00	0.04	0.17	0.00	0.02	0.04	0.00
rwy_{t-1}	0.05	0.52	0.00	0.18	0.95	0.00	0.55^{**}	1.96	0.02
wy_{t-1}	-0.25^{*}	−1.70	0.01	-1.09^{***}	−3.64	0.09	-2.22^{***}	−5.43	0.19
$divyld_{t-1}$	0.00	0.87	0.00	0.02^{**}	2.01	0.02	0.03^{**}	2.25	0.03
$spgdp_{t-1}$	−0.02	−1.29	0.01	-0.10^{***}	−2.84	0.05	-0.19^{***}	−3.83	0.10
Δur_{t-1}	−0.004	−0.17	0.00	0.02	0.43	0.00	−0.04	−0.57	0.00
φ_{t-1}	1.35	0.97	0.00	8.05^{***}	2.78	0.05	14.47^{***}	3.47	0.08
$\Delta cred_{t-1}$	0.35	1.11	0.00	0.63	0.95	0.00	0.96	0.99	0.00
$aSBRDLR_{t-1}$	−0.00	−0.86	0.00	-0.02^{***}	−3.07	0.06	−0.03	−0.81	0.00

Table 2
Forecasting real stock returns (4-quarter horizon) - agnostic approach: Quantile regressions.

	Quantile					
Predictor	2.5%	25%	50%	75%	97.5%	*p*-value
ΔC_{t-12}	−2.19	−1.17	−0.70	−0.24	0.53	0.01^{***}
wy_{t-1}	−1.40	−0.93	−0.68	−0.44	−0.02	0.00^{***}
$spgdp_{t-1}$	−0.13	−0.08	−0.06	−0.03	0.02	0.09^{*}
$aSBRDLR_{t-1}$	−0.04	−0.03	−0.02	−0.02	−0.01	0.00^{***}

Note: The Khmaladze (1981) and Koenker and Xiao (2002) test computes a joint test that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across quantiles.
** Statistically significant at the 5% level.
* Statistically significant at the 1% level.
*** Statistically significant at the 10% level.

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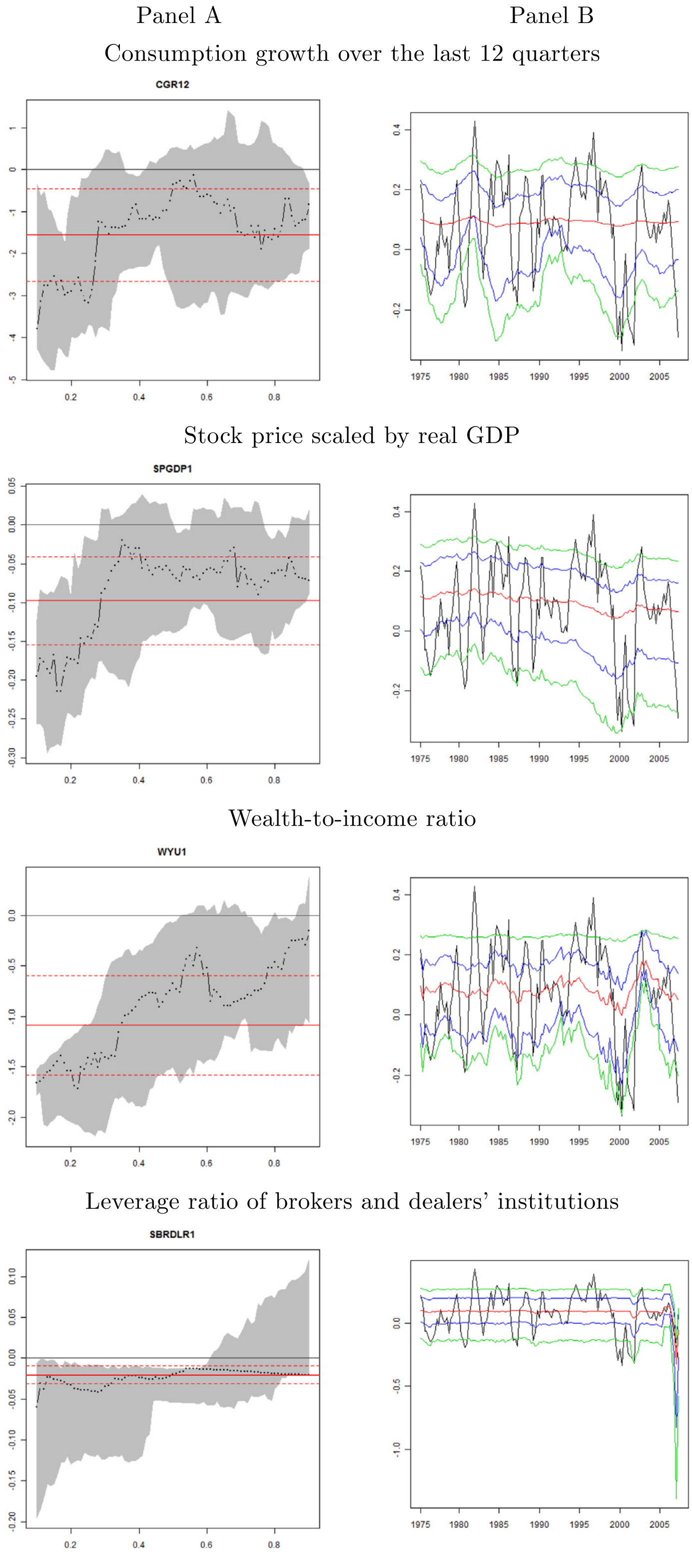

Fig. 2. Forecasting real stock returns (4-quarter horizon) - agnostic approach: Quantile regressions.

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Table 3
Forecasting real stock returns (8-quarter horizon) - agnostic approach: Quantile regressions.

Predictor	Quantile					
	2.5%	25%	50%	75%	97.5%	*p*-value
ΔC_{t-12}	−4.84	−3.88	−3.36	−2.81	−1.45	0.04**
$bond_{t-1}$	1.16	2.33	2.84	3.38	4.35	0.00***
Δm_{t-1}	−7.47	−4.26	−2.77	−1.44	1.10	0.08*
cay_{t-1}	2.19	3.72	4.58	5.45	7.19	0.05**
rwy_{t-1}	0.10	0.44	0.58	0.75	1.08	0.00***
wy_{t-1}	−2.43	−1.70	−1.36	−1.04	0.47	0.10*
$divyld_{t-1}$	−0.02	−0.00	0.01	0.02	0.04	0.00***
$spgdp_{t-1}$	−0.24	−0.16	−0.12	−0.08	−0.01	0.06*
φ_{t-1}	2.61	6.19	8.48	10.91	14.75	0.00***

Note: The Khmaladze (1981) and Koenker and Xiao (2002) test computes a joint test that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across quantiles.
* Statistically significant at the 1% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 10% level.

The data covers the period 1967:2–2008:4. In one hand, the start date is determined by the availability of data for the leverage ratio of non-bank financial intermediaries (namely, brokers and dealers' institutions). On the other hand, the end date is set to avoid biases in the computation of risk premium and the explanatory power of its various determinants which may be due to the implementation of unconventional monetary policy.

Fig. 1 displays the real stock returns, as well as the recession episodes (represented as grey areas). They suggest that real stock returns tend to decline before or at the start of a recession and significantly increase thereafter. This is in line with the findings of Lettau and Ludvigson (2001) and Sousa (2010), who highlight that there is time-variation in stock returns and risk premium is counter-cyclical.

3. Empirical results

3.1. An agnostic approach: OLS regressions

In this section, we use ordinary least squares (OLS) to estimate forecasting regressions linking stock returns to a set of explanatory variables. This can be seen as a first step towards identifying the main drivers of risk premium. Table 1 summarizes the results at different forecasting horizons (1, 4 and 8 quarters ahead). All forecasting regressions include one predictor at time.

Starting with economic activity, we find a significant effect of consumption growth over 12 quarters. However, the empirical evidence does not show any significant effect of the first lag of consumption growth. This finding is in line with the results of Parker and Julliard (2005), who find that longer-term changes in consumption - that capture the "ultimate consumption risk" -, are more relevant than contemporaneous consumption growth in explaining stock returns.

Panel A Panel B

Ratio of durable to nondurable consumption

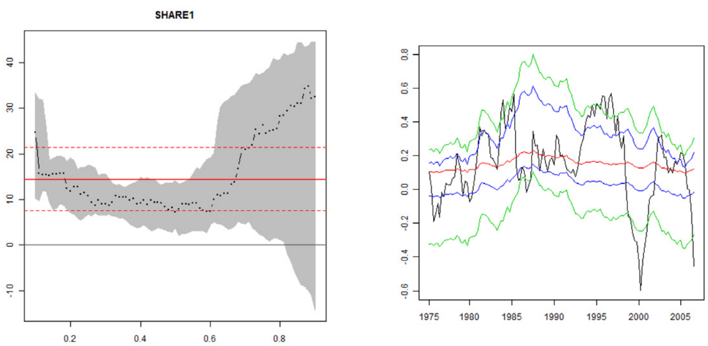

Fig. 3. Forecasting real stock returns (8-quarter horizon) - agnostic approach: Quantile regressions.

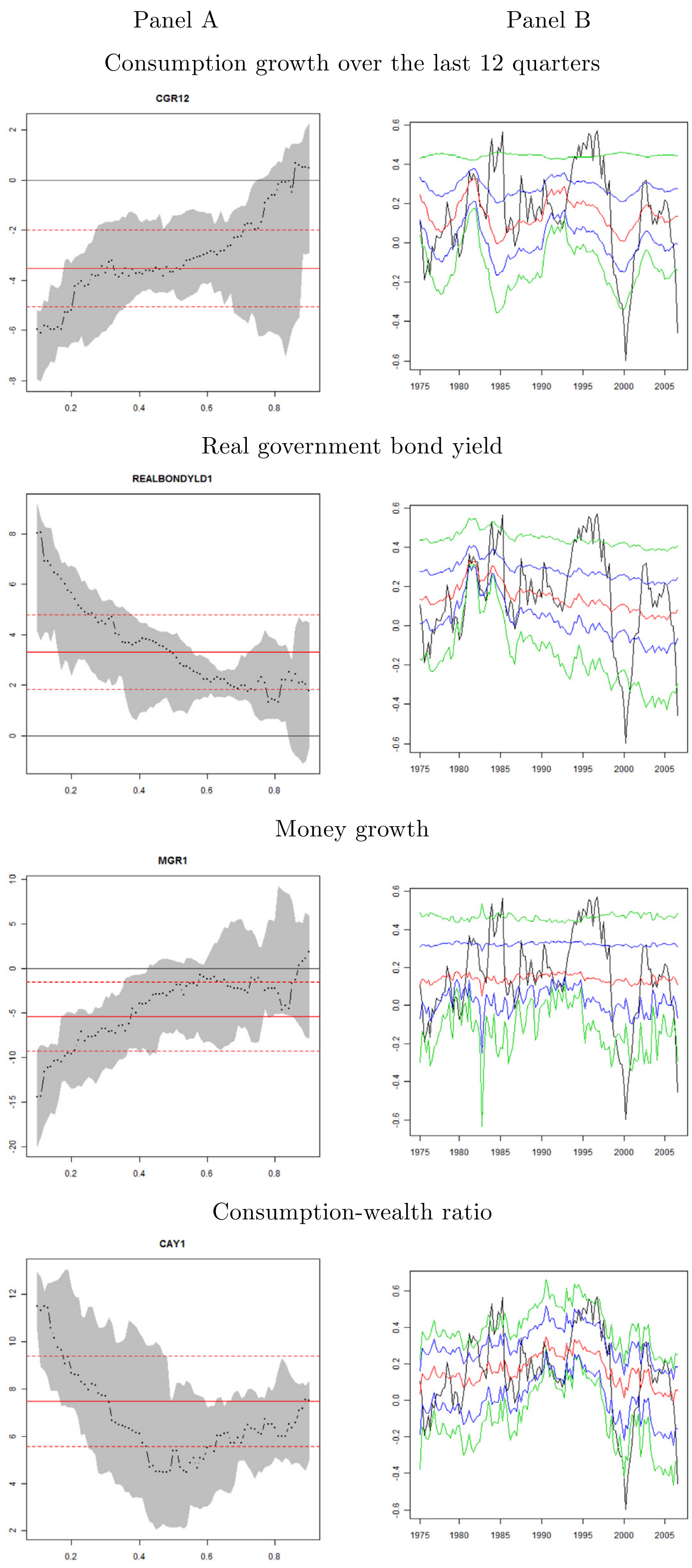

Fig. 3 (*continued*)

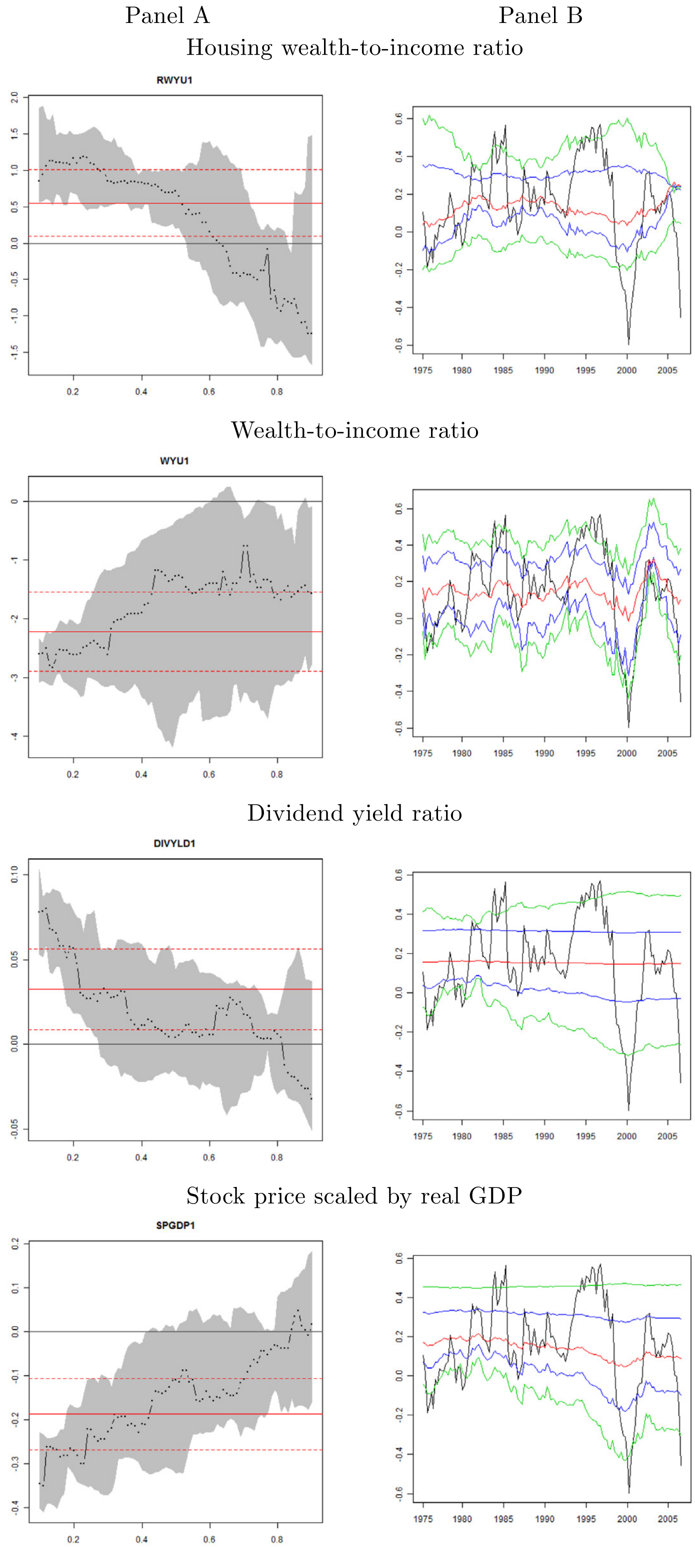

Fig. 3 (*continued*)

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Table 4
Forecasting real stock returns - asset pricing models: OLS regressions.

	Horizon		
	1	4	8
Model	$\bar{R}^2$	$\bar{R}^2$	$\bar{R}^2$
Model 1	0.04	0.10	0.17
Model 2	0.03	0.06	0.09
Model 3	0.00	0.02	0.08
Model 4	0.01	0.02	0.08
Model 5	0.00	0.09	0.17
Model 6	0.01	0.02	0.08
Model 7	0.00	0.10	0.15
Model 8	0.04	0.10	0.27
Model 9	0.05	0.17	0.39
Model 10	0.02	0.05	0.08
Model 11	0.00	0.00	0.00
Model 12	0.01	0.08	0.18
Model 13	0.00	0.09	0.24
Model 14	0.05	0.17	0.37
Model 15	0.00	0.03	0.09
Model 16	0.00	0.00	0.01
Model 17	0.00	0.00	0.00
Model 18	0.00	0.04	0.07
Model 19	0.00	0.05	0.00

With regard to prices, the results suggest that both inflation, the change in inflation and changes in commodity prices are not very informative regarding future stock returns.[5] However, fluctuations in housing prices appear to have some predictive content and the coefficient associated with this variable is negative. This result is in line with the work of Sousa (2015b), who tests the assumption of constant relative risk aversion (CRRA) using macroeconomic data and shows that the representative agent uses housing as a hedge against unfavorable wealth fluctuations.

Turning to financial variables, the change in the short-term interest rate seems to be an important predictor of stock returns, but the same does not hold for the credit growth. As for money growth, it is only marginally significant at the 8-quarter horizon. The level of the real government bond yield and the change of the real bond yield also predict stock returns.

The dividend yield has been used traditionally as a predictor of stock returns and, indeed, it is significant. As for the leverage ratio of broker and dealers' institutions, it is significant at the 4-quarter horizon. The coefficient is negative as in Adrian et al. (2010), thus, suggesting that an increase in the leverage of these institutions leads to lower stock returns.

In what concerns the macro-financial indicators, the results show that the ratio of wealth to labour income (Sousa, 2015a) and the ratio of stock prices to real GDP (Rangvid, 2006) are relevant in most of the forecasting horizons. Other important indicators are the consumption-aggregate wealth ratio (*cay*), the consumption-(dis) aggregate wealth (*cday*) and the share of durable to nondurable consumption (φ).

3.2. An agnostic approach: quantile regressions

In this section, we repeat the previous forecasting exercise using quantile regressions. In order to narrow down the number of models, we concentrate on those models where the explanatory variables are significant in the OLS equations and in, at least, one of the quantiles in the quantile regressions. We exclude those models where we cannot reject the hypothesis of the equality of the slope coefficients across quantiles (using the Khmaladze (1981) and Koenker and Xiao (2002) test) as, in such cases, the quantile approach would not represent a major advantage over the OLS procedure.

At the 1-quarter horizon, the results show that none of the models fulfills the double criteria that we set and so there is not much gain in using the quantile approach.

At the 4-quarter horizon, the following variables satisfy our double criteria: the consumption growth over the last 12 quarters (ΔC_{t-12}), the wealth-to-income ratio (wy_{t-1}), the ratio of stock prices scaled by real GDP ($spgdp_{t-1}$) and the leverage ratio of brokers and dealers' institutions ($SBRDLR_{t-1}$). Table 2 summarizes the results. Fig. 2 shows the stock returns and the implied quantiles. In Panel A, for each coefficient: (a) the dotted line shows the quantile regression estimates for quantiles ranging from 0.10 to 0.90; (b) the red[6] solid line represents the OLS coefficient; (c) the two red dashed lines depict conventional 90% confidence intervals for the OLS coefficient; and (d) the shaded grey area plots a 90% pointwise confidence band for the quantile regression estimates. In Panel B: (i) the black line plots the real returns; (ii) the green lines display the implied quantiles 0.10 and 0.90; (iii) the red line shows the implied quantile 0.50 (median); and (iv) the blue lines represent the implied quantiles 0.25 and 0.75.

[5] From an empirical perspective, Leon Li (2013) looks at the relationship between oil prices and the U.S. economy using a quantile regression approach.
[6] For interpretation of color in Fig. 2, the reader is referred to the web version of this article.

Table 5
Forecasting real stock returns (1-quarter horizon) - asset pricing models: Quantile regressions.

Model	*p*-value
Model 1	0.08*
Model 2	0.01***
Model 5	0.01***
Model 7	0.00***
Model 10	0.03**

Note: The Khmaladze (1981) and Koenker and Xiao (2002) test computes a joint test that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across quantiles.
* Statistically significant at the 1% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 10% level.

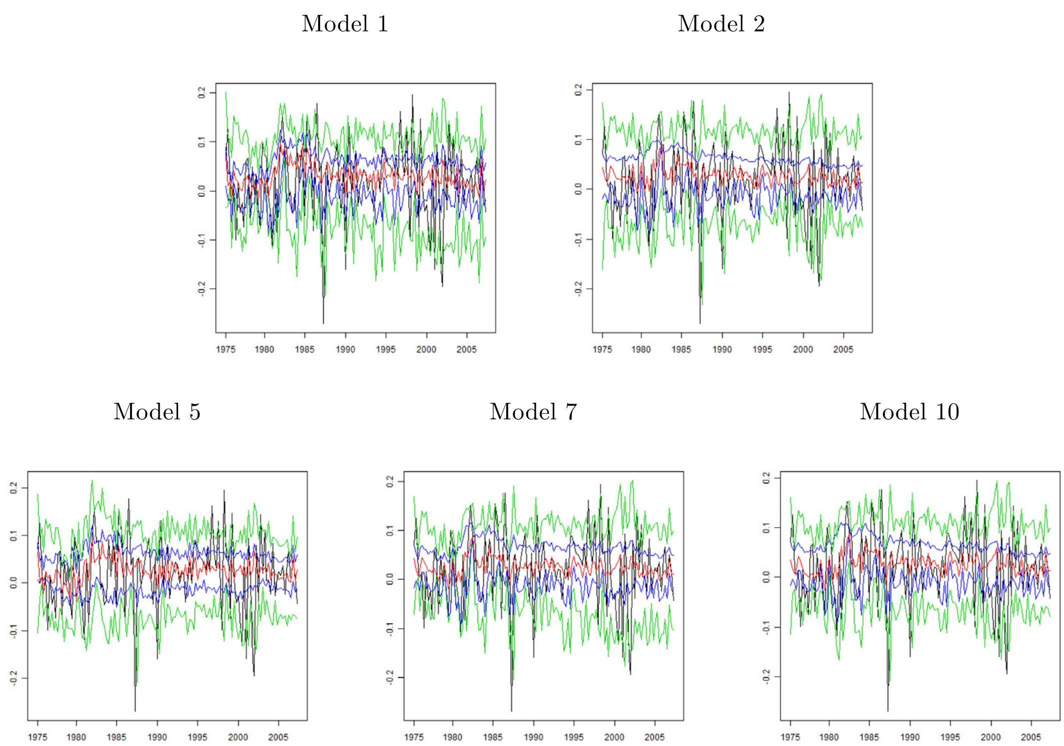

Fig. 4. Forecasting real stock returns (1-quarter horizon) - asset pricing models: Quantile regressions.

Starting with consumption growth, the estimates show that this variable helps in characterizing the lower quantiles. In line with expectations, the coefficient is negative, suggesting that long periods of higher consumption growth increase the probability of lower stock returns, again suggesting a fall in risk premium. The same happens in the case of the wealth-to-labour income ratio - but now also the quantile 0.75 is influenced -, where the coefficient is negative: when wealth increases relative to income, the likelihood of low returns also increases, which is consistent with a lower risk premium. The ratio of stock prices to GDP is also helpful in explaining the lower quantiles and also the quantile 0.75. The coefficients are all negative, thus, showing that a higher ratio of stock prices to GDP predicts a fall in future returns, in line with the work of Rangvid (2006). The leverage ratio of brokers and dealers' institutions also enters with a negative sign in the equations and this variable captures well the upper quantiles of the distribution of stock returns.

At the 8-quarter horizon, the number of models that satisfy our criteria is much larger, which suggests that stock return predictability is particularly important at the medium to long-term horizons as highlighted by Lettau and Ludvigson (2001). In particular, Table 3 and Fig. 3 suggest that the ultimate consumption risk, financial indicators (money growth, real govern-

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Table 6
Forecasting real stock returns (4-quarter horizon) - asset pricing models: Quantile regressions.

Model	*p*-value
Model 1	0.00***
Model 2	0.02**
Model 5	0.03**
Model 7	0.00***
Model 10	0.00***
Model 12	0.00***
Model 15	0.05**
Model 19	0.01***

Note: The Khmaladze (1981) and Koenker and Xiao (2002) test computes a joint test that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across quantiles.
* Statistically significant at the 1% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 10% level.

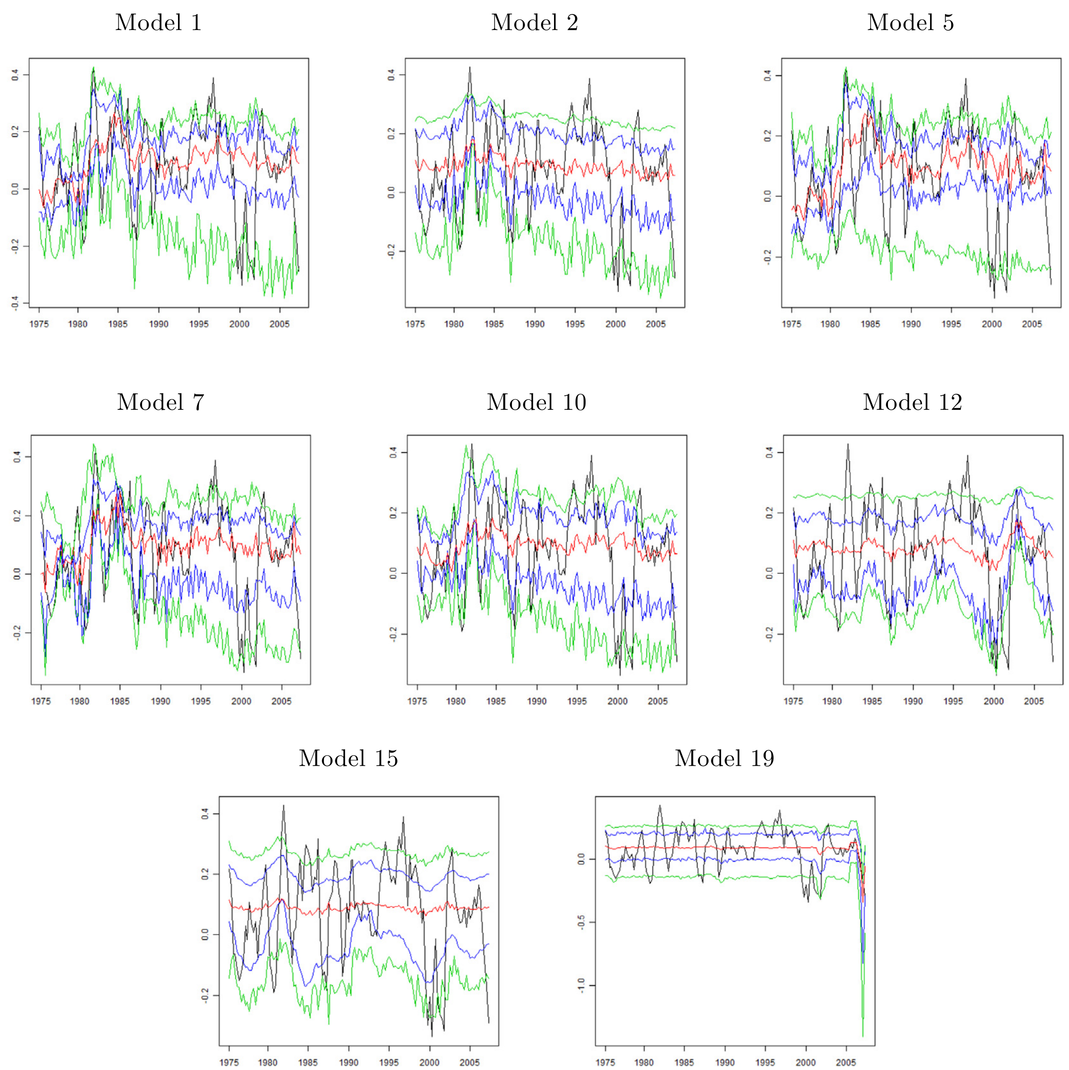

Fig. 5. Forecasting real stock returns (4-quarter horizon) - asset pricing models: Quantile regressions.

Table 7
Forecasting real stock returns (8-quarter horizon) - asset pricing models: Quantile regressions.

Model	*p*-value
Model 1	0.00***
Model 2	0.00***
Model 3	0.00***
Model 4	0.00***
Model 5	0.00***
Model 6	0.00***
Model 7	0.00***
Model 8	0.00***
Model 10	0.00***
Model 12	0.00***
Model 15	0.03**
Model 18	0.00***

Note: The Khmaladze (1981) and Koenker and Xiao (2002) test computes a joint test that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across quantiles.
* Statistically significant at the 1% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 10% level.

ment bond yield and dividend yield) and macro-financial variables (consumption-wealth ratio, housing wealth-to-income ratio, wealth-to-income ratio, stock price scaled by real GDP and ratio of durable to nondurable consumption) play a major role at capturing time-variation in risk premium.

3.3. A focus on asset pricing models: OLS regressions

In this section, we assess stock return predictability while restricting our attention to a set of asset pricing models developed in the empirical finance literature. These are based on the works of: (1) Chen et al. (1986); (2) Campbell (1987) and Ferson (1990); (3) Harvey (1989); (4) Ferson and Harvey (1991); (5) Ferson and Harvey (1993); (6) Whitelaw (1994), Pontiff and Schall (1998), and Ferson and Harvey (1999); (7) Pesaran and Timmermann (1995); (8) Julliard and Sousa (2007); (9) Julliard and Sousa (2007); (10) Bossaerts and Hillion (1999); (11) Rubinstein (1976) and Breeden (1979), i.e., the Consumption-Capital Asset Pricing Model (C-CAPM); (12) Sousa (2015a); (13) Lettau and Ludvigson (2001); (14) Sousa (2010); (15) Parker and Julliard (2005); (16) Lustig and Van Nieuwerburgh (2005); (17) Santos and Veronesi (2006); (18) Yogo (2006) and Piazzesi et al. (2007); and (19) Adrian et al. (2010). In contrast with the agnostic approach presented in Sections 3.1 and 3.2, here we focus on the listed asset pricing models. As a result, each framework may encompass more than one predictive variable. For this reason and also to ease comparison across models, lagged returns are included as a control variable even though it is well-known that asset returns are forward-looking variables.[7]

We start by considering the OLS framework and Table 4 provides a summary of the $\bar{R}^2$ statistics at different forecasting horizons (1, 4 and 8-quarters ahead). More specifically, it reports the cases where at least one of the explanatory variables is statistically significant. It can be seen that, as in the case of the univariate models, the results vary by horizon, with short-run forecasting regressions displaying less predictive power than medium to long-run forecasting regressions.

3.4. A focus on asset pricing models: quantile regressions

At the 1-quarter horizon, models 1, 2, 5, 7 and 10 have, at least one slope in the OLS regressions that are significant, and the Khmaladze (1981) and Koenker and Xiao (2002) tests suggest a rejection of the hypothesis of the equality of the slope coefficients across quantiles (see Table 5 and Fig. 4).

As in the case of the agnostic approach, when the forecasting period is horizon is increased, the number of models with significant explanatory power increases. At the 4-quarter horizon, there are eight models that fulfill the necessary criteria (Table 6). Fig. 5 shows that real stock returns and the fitted values implied by the quantile regressions. The intervals between quantiles are wide at the lower quantiles, but rather narrow at the upper quantiles. The results suggest that risk premium went down during the second half of the nineties and early 2000s, as indicated by a decline of the quantiles 0.10 and 0.25. This implies that the probability of low returns increased, in accordance with a more relaxed attitude towards risk. Following the burst of the dotcom bubble, there seems to be an upward shift in the lower quantiles, resulting in an apparently more neutral risk-taking behaviour.

[7] Indeed, Table 1 shows that the adjusted-R^2 statistics of the forecasting regressions where lagged returns are the only predictor are nil.

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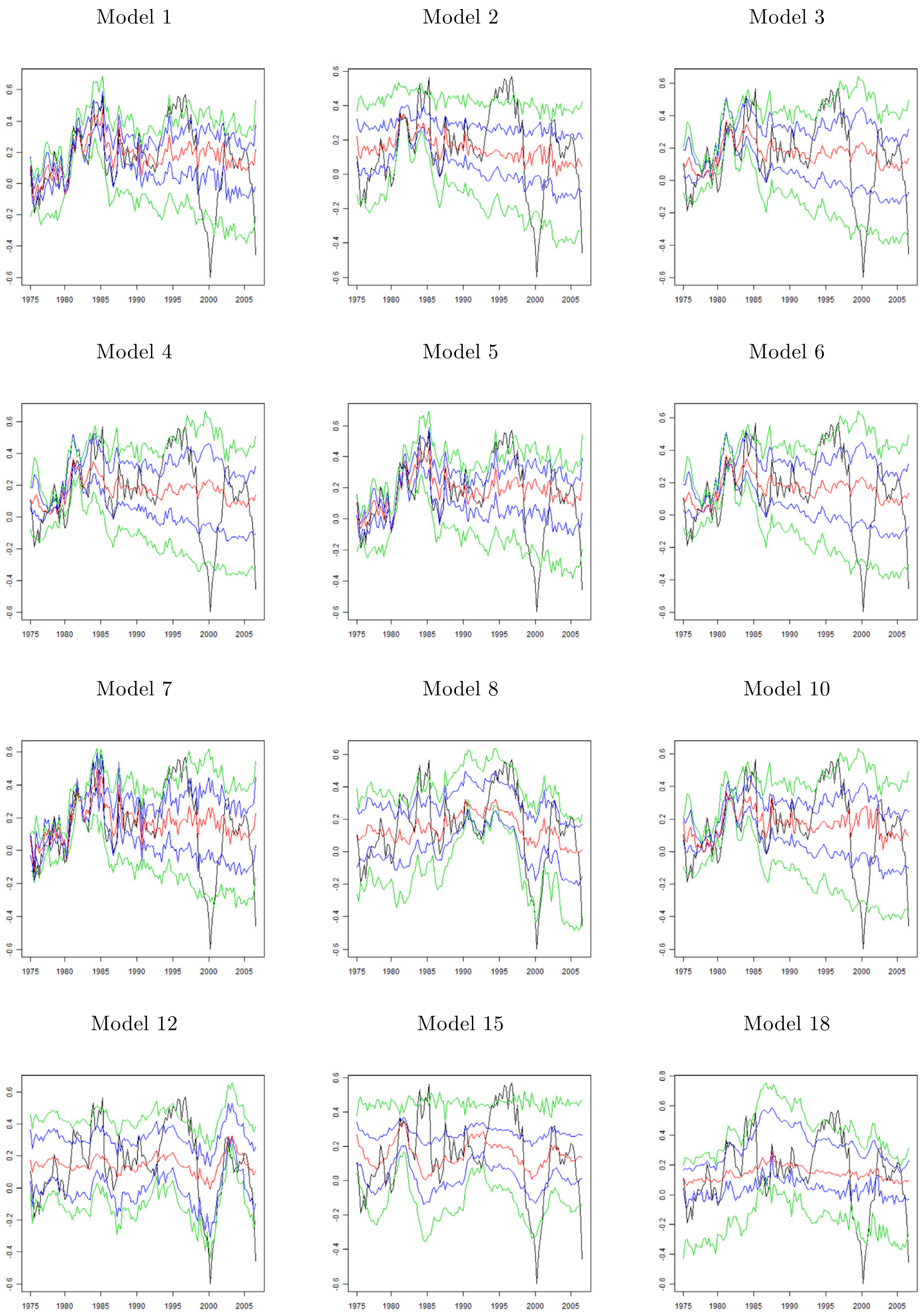

Fig. 6. Forecasting real stock returns (8-quarter horizon) - asset pricing models: Quantile regressions.

At the 8-quarter horizon, there are 12 models that satisfy the criteria. This can be seen in Table 7, which summarizes the Khmaladze (1981) and Koenker and Xiao (2002) tests.

Fig. 6 displays the real stock returns and the fitted values corresponding to the various quantiles. As before, we see that the lower quantiles are the most variable ones, in particular, the quantile 0.10. The magnitude of the estimates is also larger, suggesting that the asset pricing models under consideration are better at predicting periods of low returns. One can also observe a downward shift in the lower quantiles during the years preceding the burst of the dotcom bubble and some rise thereafter, even though the high levels of the past are not reached. The medium and upper quantiles have a more stable behaviour.

4. Conclusion

In this paper, we conduct a thorough investigation of the conditional distribution of stock returns using a quantile regression framework. We conclude that there are several variables that influence such distribution and help explaining the fluctuations in risk premium.

The results of the forecasting regressions are consistent with theoretical predictions and so monitoring these factors can help assessing attitudes towards risk. In particular, we show that the credit growth and the long-term consumption growth predict a fall in future stock returns, which suggests an increase in the exposure to risk by investors.

With regard to the evidence based on empirical asset pricing models, we find that various specifications provide support to time-variation in the probability distribution of returns. In particular, lower quantiles tend to be less stable than upper quantiles. Thus, asset pricing models track reasonably well the expectations that less risk-averse agents have about future returns.

The quantile approach used in the current work is a valuable complement to the standard approaches that are based on the ordinary least squares estimator. Indeed, by showing that the conditional return distribution can respond to factors in different ways at alternative slices of the return distribution, our framework highlights the role played by certain pricing factors at picking up episodes of extremely high (low) risk premium.

The richer characterization of the relationship between the conditional return distribution (rather than just the mean return) and various pricing factors that the quantile regression allows is also of interest to academics, policymakers and practitioners. In particular, the research presented in this paper shows that some predictors are better at tracking periods of abnormally high (low) stock returns. As asset fluctuations can degenerate in bubbles or price misalignments that may ultimately lead to financial, our results can contribute to the design of macroprudential policies by providing a battery of early warning indicators.

Moreover, in the light of the increased volume of activity of financial and institutional investors, such as commodity index funds, hedge funds and large investment banks, which are more sensitive to market risk when financial markets experience large fluctuations (Brown and Spitzer, 2005), our work can not only enhance the classification of performance-based asset portfolios but also improve the understanding of the drivers of the tails of return distribution and, thus, the management decisions of those investors (Brown and Goetzmann, 2003).

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