The fourth-quarter consumption growth rate: A pure-macro, not-estimated stock return predictor that works in-sample and out-of-sample*

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Abstract

We show that the change in real consumption from the third quarter of a calendar year to the fourth quarter contains a surprisingly large amount of information about the time-series behavior of expected excess returns on stocks, both in-sample and out-of-sample. This is interesting because the fourth-quarter consumption growth rate is a purely macroeconomic predictor not based upon estimated parameters or variables. Consistent with theory, the fourth-quarter consumption growth rate predicts the best when using the final and revised measures of consumption, as these data more precisely reveal the current level of consumption. Interestingly, however, even in real time, the fourth-quarter consumption growth rate still predicts significantly better than any of the seventeen other commonly used predictor variables with which we compare it.

Keywords: In-sample return predictability; Out-of-sample return predictability; Consumption growth

JEL-classification: E44; G12; G14

1 Introduction

The question of whether stock returns are predictable is an important one for investors, financial economists, and macroeconomists: Saving decisions, portfolio allocations, the wealth effect of consumption, and, of course, the pricing of assets all depend upon whether returns are predictable or not. The question of stock return predictability is also much discussed. One main reason is that it is generally not macroeconomic business cycle indicators that forecast stock returns, but financial indicators.[1] In particular, it is a common perception in the literature that consumption growth does not predict stock returns. To some extent this is worrying as, ultimately, movements in expected returns should be related to movements in consumption and the business cycle.

In this paper we show that, contrary to common beliefs, one specific consumption growth rate is a very strong predictor of excess returns. The consumption growth rate that predicts returns so well – in-sample and out-of-sample – is the fourth-quarter consumption growth rate, i.e. the change in real consumption from the third quarter of the calendar year to the fourth quarter.

To preview some of our main results, we find that the R^2 from an in-sample regression of next calendar year's excess stock return on the fourth-quarter consumption growth rate is 17.35%(!) for the post-WWII period. We also find that none of the other consumption growth rates predict excess returns to any noteworthy extent. The relation between consumption changes and expected future returns is negative, as in the habit-formation model of Campbell & Cochrane (1999): In times of low consumption growth, risk aversion is high such that required returns also become high.

We compare with standard equity-premium predictors, such as the dividend yield, the earnings yield, the term spread, the short interest rate, etc. The fourth-quarter consumption growth rate always stands out as a much better predictor than any of these usually employed predictor variables. The "best" of the seventeen standard predictor variables that we compare with is

[1] Surveys of the literature can be found in Campbell (2003), Cochrane (2007), and Lettau & Ludigson (2009). Regarding macroeconomic variables, Lettau & Ludvigson (2001, page 816) state that "traditional macroeconomic variables have proven especially dismal as predictive variables" and Lettau & Ludvigson (2009, page 11) argue; "If such cyclical variation in the market risk premium is present, we would expect to find evidence of it from forecasting regressions of excess returns on macroeconomic variables over business cycle horizons. Yet the most widely investigated predictive variables have not been macroeconomic variables, but instead financial indicators such as equity-valuation ratios that have forecasting power concentrated over horizons longer than the typical business cycle".

the $\widehat{cay}$-ratio of Lettau & Ludvigson (2001). The predictive $\overline{R}^2$ using the $\widehat{cay}$-ratio is 11.48%. In other words, even when the fourth-quarter consumption growth rate is a pure macroeconomic business cycle variable not based on estimated parameters (as the $\widehat{cay}$-ratio is), the fourth-quarter consumption growth rate still captures a higher fraction of the variation in future excess returns than $\widehat{cay}$ and other variables do in-sample. Combining the fourth-quarter consumption growth rate with $\widehat{cay}$ in a bivariate regression generates an $\overline{R}^2$of 22.11% – truly noteworthy for a simple linear regression predicting one-year, non-overlapping excess returns.

We also investigate how the fourth-quarter consumption growth rate predicts returns out-of-sample. Goyal & Welch (2008) question the real-time usefulness of stock return predictability by showing that it is difficult to find variables that predict excess returns out-of-sample better than the updated historical mean of excess returns does. One variable that predicts better, though, is the fourth-quarter consumption growth rate. For instance, the Campbell & Thompson (2008) out-of-sample R^2 is 14.81% when using the fourth-quarter consumption growth rate, whereas it is -7.28%, -4.47%, and 2.30% when using the first-, second-, and third-quarter consumption growth rates, respectively. Similarly, none of the other predictors that Goyal & Welch (2008) investigate do nearly as well in terms of capturing returns out-of-sample as the fourth-quarter consumption growth rate does. We also calculate the utility gains that a mean-variance investor would have received if he had used the fourth-quarter consumption growth rate to forecast returns when making portfolio allocations. We find these utility gains to be sizeable.

There are good reasons why the relation between the fourth-quarter consumption growth rate and expected returns is so strong. First, Barsky & Miron (1989) and Beaulieu & Miron (1992) document that movements in seasonally unadjusted consumption are dominated by strong increases in consumption in the fourth quarter (due to what they call the "Christmas demand shock"), followed by first quarter declines. Second, investment decisions are generally not taken continuously but at infrequent points in time because investors have to devote time and energy to studying the stock market when investing.[2] Jagannathan & Wang (2007) argue that the infrequent points in time where investors decide to review their investments are most likely influenced by culture (such as Christmas) and institutional features (such as the resolu-

[2] Abel, Eberly & Panageas (2007, 2009) study the implications of investors having to pay a utility cost for observing asset values. They show that under relatively mild conditions, it becomes optimal to observe the value of one's portfolio with a constant interval of time between observations, i.e., for instance, observe the value of the portfolio every fourth quarter of the year. Bacchetta & van Wincoop (2009) show how management fees can give rise to infrequent investment decisions which result in exchange rate predictability. Duffie & Sun (1990), Lynch (1996), and Gabaix & Laibson (2002) also study infrequent portfolio decisions.

tion of uncertainty about end-of-year bonuses and the tax consequences of capital gains and losses, which both mainly occur in the fourth quarter of the year). If the points in time where consumption and investment decisions are taken coincide, such as in the fourth quarter, the relation between consumption decisions and expected returns should become extraordinarily clear, and, indeed, this is the main finding of our paper. Similar to Jagannathan & Wang (2007), we thus provide evidence that the fourth-quarter consumption growth rate contains special and striking information about stock prices: Jagannathan & Wang document the cross-sectional implications of the fourth-quarter consumption growth rate; we highlight the time series implications.

The fourth-quarter consumption growth rate is a pure, not-estimated, macroeconomic variable. Like all macroeconomic variables, consumption data are published with a lag and are subject to revisions. We address this in the following way: Throughout our in-sample analyses we use the measure of consumption that is available today, i.e. the revised measure of consumption. This is reasonable because we want to evaluate whether the consumption decisions made in the last quarter of the calendar year reflect consumers' expectations about future stock returns. To do so, we should use the best measure of consumption, which is indeed the today-available revised measure of consumption. For investors making forecasts in real time, though, the situation is different. First, the relevant consumption series for such investors is the one available at the point in time when the forecasts were made. This consumption series is most likely different from the one we see today because of data revisions. Second, in early subsamples of the full sample, the coefficients in a forecasting equation might be different from those a researcher who has access to data covering the whole sample period finds. Hence, we proceed in two steps. First, we evaluate how our full-sample results depend upon the use of forecasting coefficients estimated over the whole sample by presenting the results from a "traditional" out-of-sample forecasting analysis where the forecasting parameters are estimated recursively using the today-available revised consumption series.[3] We find very strong out-of-sample predictability, allowing us to conclude that our in-sample results are not sensitive to the use of forecasting coefficients estimated on the full-sample. Next, we conduct investigations using real-time vintages of the data. This exercise reflects the situation of a real-time investor.

[3] This part of the analysis then, of course, does not reflect the situation of a real-time investor. It does tell us, though, how the predictability we find in the in-sample analyses depends upon the use of the full-sample to estimate predictive coefficients. Notice that Lettau & Ludvigson (2001) only use the today-available revised measure of consumption in their out-of-sample analyses. Guo (2009) shows that the out-of-sample performance of $\widehat{cay}$ is sensitive to the use of real-time data instead of today-available revised data.

We find that even if the out-of-sample forecasts using real-time data are not as precise as when using the today-available revised data, the fourth-quarter consumption growth rate still produces significantly lower forecast errors than the historical updated mean. We also find that the fourth-quarter consumption growth rate is the "best" out-of-sample forecasting variable among the many variables that we investigate. Indeed, the latter finding is a main point of our paper. We conclude that the fourth-quarter consumption growth rate also provides valuable information about future excess returns in real time.

We conduct a number of additional tests that show that our results are robust. We (*i*) analyze quarterly returns and find that the fourth-quarter consumption growth rate predicts the returns of not only one quarter during a year, but three out of four quarters. We (*ii*) predict cumulative long-horizon returns, and show that the forecasting power builds up within the calendar year, reflecting that the fourth-quarter consumption growth rate predicts different quarters of the year, but also that the fourth-quarter consumption growth rate does not predict returns more than one year ahead. We (*iii*) find that the fourth-quarter growth rate predicts returns both during periods of contractions and expansions, in contract to traditionally used variables, such as the dividend yield, that mainly predict during periods of contractions. We (*iv*) use quarterly changes of series related to consumption, such as GDP, final sales, and retail sales, to predict the equity premium and find that their fourth quarter changes are significant return predictors, whereas the changes in the other quarters are not significant. Finally, we (*v*) use a VAR to analyze the effects on returns, dividend yields, and dividend growth rates resulting from a shock to the fourth-quarter consumption growth rate. This helps us understand why the fourth-quarter consumption growth rate predicts so strongly: The information it contains is about excess returns and not about cash-flows.

Related literature. As already mentioned, we are not the first to draw attention to the special asset-pricing implications of the fourth-quarter consumption growth rate. The most important predecessors to our work are Jagannathan & Wang (2007) who show that a consumption-based asset pricing model describes the cross-sectional variation in excess returns well when using the fourth-quarter consumption growth rate to estimate the consumption betas, whereas betas estimated using the consumption growth rates of other quarters do not line up against average excess returns. Jagannathan & Wang (2007), thus, focus on the cross-section of returns; we focus on the time-series of returns.

One of us (Møller, 2008) has earlier provided initial evidence on the extraordinary predictive power of the fourth-quarter consumption growth rate using simple annual in-sample regressions. We extend the preliminary in-sample analysis in Møller (2008) in many directions. First of all, we show that the fourth-quarter consumption growth is also an interesting predictor of returns out-of-sample. In Møller (2008), there are no out-of-sample analyses. Second, regarding the in-sample analyses, we show that the timing of returns are not important for the conclusions we draw by investigating quarterly returns, annual returns measured over different four-quarter intervals, long-horizon regressions, and other issues. We also show that the fourth-quarter growth rates of other macroeconomic variables such as GDP and sales predict returns. Finally, we analyze in more detail why the fourth-quarter consumption growth rate is such a strong predictor of returns. All in all, we provide a considerably deeper investigation of the in-sample results than Møller (2008) did and we provide out-of-sample investigations (that were not considered in Møller, 2008) that also take data revisions into account.

After Goyal & Welch (2008), a set of papers have shown that one can *estimate* variables that predict excess returns out-of-sample better than a constant. For instance, Ferreira & Santa-Clare (2009) show that if the different components of returns (dividend yields, earnings growth, and growth in the price-earnings ratio) are estimated separately, the resulting sum predicts better than a constant out-of-sample. Santa-Clara & Lacerda (2009) adjust the dividend-price ratio by removing an estimate of the expected dividend growth rate, and find that the adjusted dividend-price ratio predicts better than a constant out-of-sample. Cooper & Priestley (2009) estimate the potential level of output and use it to construct the output gap that also predicts well out-of-sample. Compared to these variables, the advantage of the fourth-quarter consumption growth rate is that it is not based on any estimation and can be used directly as it is.

The fourth-quarter consumption growth rate is a pure macroeconomic variable. Hence, our paper is also related to the branch of the literature that promotes the use of macroeconomic variables when predicting excess returns, the argument being that such variables directly link the predictive power they contain to the business cycle. An advantage of the fourth-quarter consumption growth rate is that it does not utilize the stock price itself and, hence, should not suffer from any "fad" in stock prices being corrected over time, in contrast to the price-output ratio of Rangvid (2006), for instance. Likewise, the fourth-quarter consumption growth rate does not require an estimation of a "natural" or "potential" level of output, as the output gap of

Cooper & Priestley (2009) does, nor does it require an estimation of cointegration parameters, like the $\widehat{cay}$-ratio of Lettau & Ludvigson (2001) does.

The rest of the paper proceeds as follows. In the next section, we describe the data that we use. After this, we examine the in-sample predictive power of the fourth-quarter consumption growth rate, followed by an out-of-sample analysis in Section 4. In Section 5, we investigate specifically how the fourth-quarter consumption growth rate predicted during the financial crisis of 2008-2009. We conclude in Section 6.

2 Data

The main time series that we focus on in this paper are the consumption growth series and the excess returns on stocks series. The quarterly U.S. consumption series is available from the first quarter of 1947 to the last quarter of 2007.[4] Our first observation of the fourth-quarter consumption growth rate is the one from the third to the fourth quarter of 1948 and the last is the one from the third to the fourth quarter of 2007.[5] We reserve the financial crisis of 2008 and 2009, containing the largest stock market crash in our sample (in 2008) and an astonishing turnaround in 2009, to a separate analysis in Section 5. As we show in that section, including 2008 and 2009 into the general analysis will not change the overall picture, but we gain additional insights by presenting the results for 2008 and 2009 on their own.

Consumption is measured as the seasonally adjusted real per capita expenditures on nondurables and services. These consumption data are obtained from the Bureau of Economic Analysis. To calculate per capita figures, we use the population figures from the Bureau of Economic Analysis. It should be mentioned that our results are basically unaffected if we use aggregate consumption instead of per capita consumption.

We use the CRSP value-weighted index including NYSE, AMEX, and NASDAQ stocks to calculate the returns on stocks. From this we subtract the 3-months Treasury Bill rate in order to calculate the excess returns on stocks.[6] We provide the consumption and return data

[4] Given that the point of the paper is to focus on fourth-quarter consumption growth, we obviously have to rely on quarterly data and, hence, cannot extend the data further back in time.

[5] We start in 1948 rather than in 1947 as we compare the fourth-quarter consumption growth rate with the growth rates in the other quarters, and the first-quarter consumption growth rate is available starting from 1948. Using also the fourth-quarter of 1947 does not change the results qualitatively, but will of course change them quantitatively.

[6] We have also estimated our regressions using S&P 500 returns instead of CRSP returns. The results using

on the following webpage in order to promote easy verification and extension of our results: http://staff.cbs.dk/JRangvid/G4_Data.xls.

Benchmark predictive variables. We want to evaluate whether the fourth-quarter consumption growth series captures excess returns in-sample and out-of-sample. We also want to compare the predictive performance of the fourth-quarter consumption growth series with the predictive performance of a set of commonly used predictive variables. In our list of benchmark predictive variables, we include two standard predictive variables: the dividend-price ratio, DP, see, e.g., Campbell and Shiller (1988) and Fama and French (1988, 1989), and the spread between long-term government bond yields and Treasury bill yields, TMS, see, e.g., Campbell (1987) and Fama and French (1989). DP is calculated as the ratio between the CRSP dividends and the CRSP value-weighted stock index: when predicting next calendar year's return, we calculate DP as the accumulated dividends paid out during the previous twelve months divided by the end-of-the-year value of the CRSP value-weighted stock index. TMS is obtained from Amit Goyal's website, and we also use its end-of-the-year value. In addition, we use two newer predictor variables: the equity share in new issues, $EQIS$, proposed by Baker and Wurgler (2000), and the cointegration residual $\widehat{cay}$, which is the estimated consumption-wealth ratio proposed by Lettau and Ludvigson (2001). Goyal and Welch (2008) conclude that $EQIS$ is the most successful among the comprehensive list of predictive variables applied in their study. $EQIS$ and $\widehat{cay}$ are obtained from Amit Goyal's website. All benchmark predictive variables are measured on an annual frequency. As robustness checks, we also compare with a host of additional predictive variables sometimes used in the literature, see Section 4.4.1.

2.1 Summary statistics and plots

Table 1 reports summary statistics of consumption growth rates and benchmark predictive variables. $G^{c,i}$ is the consumption growth rate during the ith quarter, i.e. $G_t^{c,4}$ is the fourth-quarter consumption growth rate calculated from the third quarter in year t to the fourth quarter in year t. The table shows that $G^{c,4}$ has a slightly higher standard deviation and range (Max value minus Min value) than the consumption growth rates based on the first, second, and third quarters. The table also shows that $G^{c,4}$ has a very low degree of persistence, like the consumption growth series from the other quarters. The AR(1) coefficient of $G^{c,4}$ is

S&P 500 are almost identical to the results we show in the paper.

0.005. This low degree of persistence of the consumption growth series is important because it implies that predictive regressions using $G^{c,4}$ (and the other consumption growth rates) as the explanatory variable will not suffer from the statistical problems that otherwise arise when using a highly persistent predictive variable, cf. Stambaugh (1999). The persistence of the consumption growth rate can be compared to the persistence of the benchmark variables. The dividend yield, for instance, has an AR(1) coefficient of 0.905. The benchmark variable with the lowest persistence is the term spread. The AR(1) coefficient of the term spread is, however, almost 100 times larger than the AR(1) coefficient of the fourth-quarter consumption growth series.

Figure 1 plots $G^{c,4}$ with shaded areas representing the NBER recession periods. The figure shows that $G^{c,4}$ rises during business cycle expansions and reaches its highest values near peaks, while it falls during business cycle contractions and reaches its lowest values near troughs. As we show below, $G^{c,4}$ predicts returns well. The clear business cycle pattern revealed in Figure 1 suggests that $G^{c,4}$ tracks time variation in expected returns over the business cycle; low consumption growth rates at business cycle troughs coincide with high expected returns, and high consumption growth rates at business cycle peaks coincide with low expected returns.

Panel B of Table 1 shows the correlations between the series. It is seen that $G^{c,4}$ is not much correlated with any of the other series (the highest correlations are with the third-quarter consumption growth rate and $\widehat{cay}$ where the correlations are 0.30 and 0.27, respectively, in numerical terms), i.e. $G^{c,4}$ contains unique information.

3 In-sample predictive regressions

We first document that $G^{c,4}$ is a strong predictor of excess returns in-sample. We do so by running standard in-sample predictive regressions:

$$R^e_{t+1} = \alpha + \beta X_t + e_{t+1}, \tag{1}$$

where R^e_{t+1} is the one-period ahead excess stock return and X_t is the predictive variable.

3.1 One-year ahead predictive regressions

Table 2 shows the first results.[7] In the table, we show results from regressing one-year ahead excess returns on the predictor variables. The timing used in the regressions in Table 2 is as follows: for $G^{c,1}$, the one-year ahead excess stock return is measured from the beginning of the second quarter to the end of the first quarter next year; for $G^{c,2}$, the one-year ahead excess stock return is measured from the beginning of the third quarter to the end of the second quarter next year; and likewise for $G^{c,3}$. For $G^{c,4}$, DP, TMS, $EQIS$, and $\widehat{cay}$, the one-year ahead excess stock return is measured over the calendar year. For each regression, the table reports the slope estimate, the Newey and West (1987) corrected t-value, and the adjusted R^2-statistic.

The results are clear. $G^{c,4}$ is highly statistically significant with a Newey-West corrected t-value of -5.68 and it explains 22.91% of the variation in one-year ahead excess stock returns. This is a very big $\bar{R}^2$ for a predictive regression.[8] Indeed, when the consumption growth rate of any other quarter is used as a predictor, the predictive power breaks down; the slope estimates are insignificant (or borderline significant) and the $\bar{R}^2$-statistics are close to zero or negative.

The fraction of expected excess return variation captured by the fourth-quarter consumption growth series becomes even more impressive when compared to the performance of traditionally used predictor variables. First, TMS does not contain significant in-sample predictive power in the post-war sample that we use here. Second, DP, $EQIS$, and $\widehat{cay}$ are significant, but DP and $EQIS$ only produce single-digit adjusted $\bar{R}^2$-statistics (of, respectively, 9.13% and 4.50%).[9] The only variable that produces a two-digit $\bar{R}^2$-statistic is $\widehat{cay}$. It is important to remember, though, that $\widehat{cay}$ is an estimated predictor. When using $\widehat{cay}$ in in-sample regressions, it is, thus, implicitly assumed that the forecaster knows the cointegration parameters that have been used to construct $\widehat{cay}$, i.e. the results based upon $\widehat{cay}$ potentially suffer from a look-ahead bias.[10] On

[7] This table is basically an update of Table 2 in Møller (2008). We show this table (and Table 1 with summary statistics) also here in order to provide the full picture. The remaining tables in this paper are new in relation to Møller (2008).

[8] In Section 5, we show that the R^2 is 17.35% when including the crisis of 2008 and 2009. We also show that this is still considerably higher than for commonly used predictor variables; for instance, the R^2 using $\widehat{cay}$ drops to 11.48% when including 2008 and 2009. Hence, the results are qualitatively unaffected by including 2008 and 2009.

[9] As Table 1 showed, DP, $EQIS$, and $\widehat{cay}$ are persistent variables. We could have adjusted the t-statistics in these regressions for the Stambaugh (1999) bias following for instance the procedure of Amihud & Hurvich (2004). Adjusting for the Stambaugh bias, however, would only reduce the significance of DP, $EQIS$, and $\widehat{cay}$, making the relative performance of $G^{c,4}$ even more impressive.

[10] We could have generated recursively updated cointegration parameters using the data for asset wealth, consumption, and labor income available on Martin Lettau's home page. This would have reduced the performance of $\widehat{cay}$, though, and – again – would only have made the performance of $G^{c,4}$ even more impressive.

the contrary, the fourth-quarter consumption growth series is not an estimated predictor, i.e. there is no look-ahead bias involved in using $G^{c,4}$. In addition, the $\bar{R}^2$ from the $G^{c,4}$ regression is 52% higher than that from the $\widehat{cay}$ regression (22.91% versus 15.09%). All in all, compared to standard predictor variables, the fraction of expected return variation captured by $G^{c,4}$ is impressive.

As Table 1 showed, $\widehat{cay}$ and $G^{c,4}$ are not much correlated, i.e. they should contain independent information about future returns. To check whether this is so, we run a bivariate regression with $\widehat{cay}$ and $G^{c,4}$ as explanatory variables. The results are shown in the lower part of Table 2. As expected, both $\widehat{cay}$ and $G^{c,4}$ stay significant, and the explanatory power is increased to 30.3%. We believe this is an impressive $\bar{R}^2$ when taking into account that this is a one-period return predicting regression not using overlapping observations or anything the like.

3.2 In-sample robustness checks

Having seen the first results, one would like to know if they are robust. After showing in this section that they are, we turn to an explanation of the results we find.

3.2.1 Moving returns forward by one quarter

In Table 2, we investigate how the change in consumption from the third quarter of a year to the fourth quarter can predict the returns obtained from the beginning to the end of the next calendar year, i.e. returns during the Q1-Q4 period. This is the best way to capture the relation between consumers' actually consumption decisions in the fourth quarter and their expectations about future returns. Like other macroeconomic variables, however, the level of consumption in the fourth quarter of a year is published with a lag implying that it is actually not known during the first months of the next year. Hence, we ran regressions where we moved the return we predict forward by one quarter, such that we used $G^{c,4}$ to predict the one-year return arising from the beginning of the second quarter of the next year to the end of the first quarter one year after, i.e. returns during the Q2-Q1 period (in Sections 4 and 5, we consider out-of-sample forecasts – in those forecasts we always use returns the Q2-Q1 period when using $G^{c,4}$ to predict). We found an $\bar{R}^2$ of 15.62% and a t-statistic of -3.95. Likewise, when using $G^{c,1}$, $G^{c,2}$, and $G^{c,3}$, we have also moved the returns one quarter forward compared to Table 2. We found results like in Table 2, i.e. that the other quarters do not contain nearly as high

predictive power as does $G^{c,4}$ (results available upon request).

3.2.2 What quarter does $G^{c,4}$ capture?

Given the fact that the fourth-quarter consumption growth rate is measured once each year, we focus on annual return predictions in this paper. Nevertheless, one would like to know whether $G^{c,4}$ mainly contains information about the returns of one particular quarter within the calendar year, such as the first quarter, or whether it captures the returns of several quarters within the calendar year.[11] To gain further understanding of this, Table 3 shows predictive regressions for each quarter of a calendar year. The main point to notice from the table is that the fourth-quarter consumption growth rate captures the return of not only one quarter within a calendar year, but is a significant predictor of both first-, second-, and fourth-quarter excess returns.

3.2.3 Long-horizon return predictions

When $G^{c,4}$ captures the returns of several of the quarters within the year, it seems natural to investigate whether the predictive ability of $G^{c,4}$ increases with the forecasting horizon and predicts cumulative long-horizon returns. Hence, in Table 4, we present results from long-horizon regressions $R^e_{t,t+h} = \alpha + \beta X_t + e_{t+1}$, where $R^e_{t,t+h}$ is the excess return obtained over h quarters.

We find that the predictive power of $G^{c,4}$ increases with the forecasting horizon during the first year; for $k = 1$, the $\bar{R}^2$ is 5.55%, for $k = 2$, the $\bar{R}^2$ is 8.30% etc.[12] The $\bar{R}^2$ peaks at $k = 4$. These results indicate that $G^{c,4}$ is a strong predictor of medium-term (up to one year) returns, but not longer-term returns. This is different from results in the literature using persistent predictors, such as the dividend yield. The $\bar{R}^2$s and t-statistics from regressions using persistent predictors mechanically increase with the horizon, and one has to take good care to make sure that the predictive ability captured by persistence predictors is not a statistical artifact.[13] $G^{c,4}$ is not a persistent predictor, however, as shown in Table 1. For this reason, the

[11] For instance, if $G^{c,4}$ only captures the return arising during the first quarter of a year, one could fear that it is simply a January effect that $G^{c,4}$ captures. As $G^{c,4}$ also predicts returns from the beginning of the second quarter and one year forward, as just mentioned, this is not the case.

[12] Notice the difference between the results in Tables 3 and 4. In Table 4, we show predictions of cumulative returns, whereas in Table 3, we show predictions of each single calendar quarter return.

[13] Several papers discuss the potential biases that arise in long-horizon predictive regressions when the predictor is persistent: see, for instance, Valkanov (2003), Campbell & Yogo (2006), or Boudoukh *et al.* (2008).

fact that the $\bar{R}^2$ rises with the horizon up to $k = 4$ simply reflects that $G^{c,4}$ captures the returns of the different quarters of a year: the R^2 from the regression using a one-year excess return is close to the sum of the quarterly $\bar{R}^2$s from Table 4: $5.55\% + 3.26\% + 1.69\% + 7.80\% = 18.3\%$.

Additionally, Table 4 reveals that none of the other quarterly consumption growth rates come even close to generating as high an $\bar{}$

returns during both expansions and contractions. To show this, we run the following regression:

$$R^e_{t+1} = \alpha_C I_t + \alpha_E (1 - I_t) + \beta_C I_t G^{c,4}_t + \beta_E (1 - I_t) G^{c,4}_t + \varepsilon_{t+1}$$

where I_t is a dummy equal to one if period t is a period of contraction and zero otherwise. We use the dates for contractions and expansions as defined by the NBER Business Cycle Dating Commission. Consequently, β_C captures how $G^{c,4}_t$ predicts during contractions and β_E how it predicts during expansions.

The estimate of β_C is -4.04 with a t-statistic of -1.92 (significant at the 10% level) and the estimate of β_E is -4.19 with a t-statistic of -4.36. The $\bar{R}^2$ is 20.1%, which is not much different from the one reported in Table 2.

Compare this to what is found if using, for instance, the dividend yield. Using the dividend yield, the estimate of β_C is 0.38 with a t-statistic of 4.37 and the estimate of β_E is 0.02 with a t-statistic of 0.38. The $\bar{R}^2$ of this model is 17.4%, which is very different from the one reported in Table 2. Hence, the dividend yield predicts well during contractions, but not at all during expansions, as first shown by Rapach *et al.* (2010) and Henkel *et al.* (2010).

It is comforting to know that $G^{c,4}_t$ has forecasting power during both recessions and expansions: If the forecasting power of a variable is confined to periods of contractions only, then, if using the variable in real time, one must first estimate the probability that the economy is contracting before knowing whether the variable helps predict returns. This is arguably more difficult than using a variable such as $G^{c,4}_t$ that forecasts during both expansions and contractions.

3.3 Understanding the results

In this section, we show that the fourth-quarter consumption growth rate does not predict cash-flows. This helps understanding why its predictive power for returns is so strong. Next, we discuss the actual, not-seasonally adjusted, consumption decisions taking in the different quarters. Finally, we discuss the sign with which $G^{c,4}_t$ predicts returns.

3.3.1 Return identity

Does $G_t^{c,4}$ also predict cash-flows? To answer this question, and see why it is relevant, it is useful to remember the Campbell-Shiller (1988) log-linearization of returns which implies that in the no-bubble situation, the dividend yield reflects expectations of returns, dividend growth rates, and next-period dividend yields:

$$d_t - p_t = E(r_{t+1}) - E(\Delta d_{t+1}) + \rho E(d_{t+1} - p_{t+1}) \tag{2}$$

where ρ is the linearization constant. The dividend-yield at any particular point in time thus implies a certain expected return, expected dividend growth rate, and expected dividend yield. Cochrane (2008) notices that if using additional variables, included in some information set Ω_t, to predict returns, the identity $d_t - p_t = E(r_{t+1} \,|\Omega_t) - E(\Delta d_{t+1} \,|\Omega_t) + \rho E(d_{t+1} - p_{t+1} \,|\Omega_t)$ must still hold. In other words, if a variable helps forecasting returns, it must also forecast dividend growth and/or dividend yields.

In order to investigate what variables move after $G_{t+1}^{c,4}$ has changed, the upper half of Table 5 presents results from the estimation of a first-order *VAR*, $\mathbf{X}_{t+1} = \alpha + \Phi\mathbf{X}_t + \varepsilon_{t+1}$, where $\mathbf{X}_{t+1} = \left[r_{t+1}, \Delta d_{t+1}, dp_{t+1}, G_{t+1}^{c,4}\right]'$ collects the vector of variables (the variables entering the definition of returns and the forecasting variable we focus on here: $G_{t+1}^{c,4}$) and $\varepsilon_{t+1} = \left[\varepsilon_{t+1}^{r}, \varepsilon_{t+1}^{\Delta d}, \varepsilon_{t+1}^{dp}, \varepsilon_{t+1}^{G^{c,4}}\right]'$ collects the shocks to the variables. The table shows that a change in $G_t^{c,4}$ significantly reduces next period returns with 3.29, insignificantly increases dividend growth with 0.21, and significantly increases next period dividend yields with 3.55, i.e. the identity in Eq. (2) holds ($\Delta dp \approx -3.29 - 0.21 + \rho 3.55 \approx 0$, as ρ is close to but slightly smaller than one).

The one-period return identity/approximation can be iterated forward such that it turns into statements about the long-run effects on returns and dividend growth rates from a shock to a forecasting variable: $d_t - p_t = E\left(\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} \,|\Omega_t\right) - E_t\left(\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} \,|\Omega_t\right)$. The lower half of Table 5 shows the responses of the variables to a one-unit shock to $G_t^{c,4}$. It is seen that the effect of a shock to $G_t^{c,4}$ on returns is short-lived: the big effect on returns occurs within one year, in line with what we found in Table 4 where we presented results from direct long-horizon regressions. On the other hand, the effect on dividend yields is very persistent and only slowly decaying. In combination with the fact that $G_t^{c,4}$ is not persistent at all (the

responses of $G_t^{c,4}$ to a shock to $G_t^{c,4}$ are very close to zero), these slowly decaying dividend yield responses imply that the responses of returns become small and positive after one period (the relation between dividend yields and returns is positive, though insignificant, as can be seen from the upper part of the table). In the long run, the large first-period drop in returns is thus counterbalanced by small subsequent increases in returns, such that $E\left(\sum_{j=1}^{\infty}\rho^{j-1}r_{t+j}\,|\Omega_t\right)$ becomes close to zero. The reason why $G_t^{c,4}$ does not predict dividend growth on the long run is thus simple: After a shock to $G_t^{c,4}$, it first predicts a big negative drop in returns, followed by a long series of very small positive increases due to a big initial increase in dividend yields, dividends being persistent, and the very small relation between dividend yields and returns. This is different from $\widehat{cay}$, for instance, that predicts dividend growth but not dividend yields (Lettau & Ludvigson, 2005), but helps understanding why $G_t^{c,4}$ predicts returns so strongly: The information $G_t^{c,4}$ contains is purely about expected returns and not about cash-flows.[14]

3.3.2 Seasonally unadjusted consumption growth rates

Consumption data are, in their seasonally unadjusted form, characterized by large seasonal fluctuations; see Barsky & Miron (1989) and Beaulieu & Miron (1992). Given that asset-market data are not characterized by such strong seasonal patterns, it is standard practice to use seasonally-adjusted consumption series when relating asset-market data to consumption fluctuations.[15] The actual consumption, however, is non-adjusted. Hence, we take a closer look at these in this section.

The seasonally unadjusted consumption series are available for the period from 1947 until 2004 only, as the Bureau of Economic Analysis has informed us that it has "discontinued the not-seasonally adjusted estimates for 2005 forward due to previous budget constraints". We show the seasonally unadjusted series in Figure 2. The strong seasonality is obvious, with spikes in the fourth quarters and drops in the first. Comparing the average annualized quarterly real per capita not-seasonally adjusted consumption growth rates with one another, one sees that the fourth quarter is special: The average growth rate was 23.47% during the fourth quarter,

[14] We also investigated whether $G_{t+1}^{c,4}$ predicts future changes in consumption. It does not.

[15] In this light, it is not surprising that Ferson & Harvey (1992) find that the equity premium puzzle is not "solved" by using seasonally unadjusted consumption data. It is also not surprising that the very strong seasonality of the non-adjusted consumption series make them insignificant in predicting returns (results available upon request). In other words, it is the nondeterministic changes in consumption (the seasonally adjusted changes) that have implications for expected returns. What the seasonally unadjusted series do for us, though, is that they make clear that the actual consumption decisions taken in the fourth quarter are very different from the consumption decisions taken during the rest of the year.

1.00% during the third, 12.63% during the second, and −27.63% during the first.[16] In other words, consumers decide to increase their consumption a lot in the fourth quarter, and then reduce it afterwards (during the first quarter), whereas the changes in the second and the third quarter are not as pronounced. Beaulieu & Miron (1992) conclude that it is the "Christmas demand shock" that makes consumption in the fourth quarter so special.

Given the strong seasonality of the non-adjusted consumption, we would expect to find that the fourth-quarter growth rate of (seasonally adjusted) series that are much affected by consumption should also predict returns. Hence, we run regressions of excess returns on quarterly changes in real GDP, real final sales, and real retail and food services sales, all seasonally adjusted. We show the results in Table 6. We find a surprisingly robust pattern: Changes in the fourth quarter of the year predict next year's equity premium, whereas none of the other quarters predict future risk premiums. Hence, it is not only consumption growth in the fourth quarter that predicts so well; the fourth quarter growth rate of other macroeconomic series also contain information about future risk premiums (a finding that should also reduce concerns about data snooping: It is not just one variable that shows this feature, but several variables).

3.3.3 Comparing signs

We estimate predictive regressions and find that consumption growth is *negatively* related to *future* returns, i.e. we find that beta is negative in the regression: $R^e_{t+1} = \alpha + \beta G^c_t + e_{t+1}$. Jagannathan & Wang (2007) estimate consumption betas and find that consumption growth is *positively* related to *contemporaneous* returns, i.e. they find that beta is positive in the regression: $R^e_{t+1} = \alpha + \beta G^c_{t+1} + e_{t+1}$.[17]

One model that shares these features, for instance, is the habit-formation model of Campbell & Cochrane (1999). To see this, recall the central first-order condition in the Campbell & Cochrane model:

$$E_t \left[\left(\frac{S_{t+1}}{S_t} \frac{C_{t+1}}{C_t} \right)^{-\gamma} R^e_{t+1} \right] = 0 \tag{3}$$

[16] The unadjusted series are nominal, so we have deflated with the CPI. The CPI is available in both an adjusted and an unadjusted form. Given that the seasonal behavior of prices is not large, it is not important whether we deflate with the adjusted or (as we do here) the unadjusted CPI.

[17] To make sure that we also find positive consumption betas over the sample period we use (which is slightly longer than the one Jagannathan & Wang use), we also estimate consumption betas relating consumption growth rates to contemporaneous returns. We find these estimates to be positive, like in Jagannathan & Wang (2007). The estimates are available upon request.

where S_t is the "surplus consumption ratio" defined by $S_t = 1 - X_t/C_t$ and X_t is the level of habit which is determined by past levels of consumption. Scrutinizing the $E_t\left[\left(\frac{S_{t+1}}{S_t}\right)^{-\gamma} R^e_{t+1}\right] = 0$ part of Eq. (3), i.e. keeping future growth in consumption constant for illustrative purposes, a fall in consumption today lowers the surplus consumption ratio today and, hence, $E_t\left[R^e_{t+1}\right]$ increases in order to satisfy Eq. (3). The economic mechanism is that a fall in consumption today relative to past consumption pushes up risk aversion today which increases required future returns, i.e. a negative relation between past consumption growth and expected returns. This is what we find: when consumption in the fourth quarter is low relative to the third quarter, next year's required excess return is high.

At the same time, Eq. (3) also contains the standard $E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} R^e_{t+1}\right] = 0$ term which gives rise to the positive contemporaneous relation between consumption growth and returns that Jagannathan & Wang (2007) find: if consumption is low today and the expectation about next period consumption unchanged, marginal utility of consumption today is high in relation to marginal utility tomorrow, implying that expected returns are pushed up to compensate investors for taking on stock market risk.

We do not want to push this too far, as we have no ambition of testing the habit-formation model of Campbell & Cochrane (1999).[18] We only want to notice that our finding that low growth of consumption in the past predicts high future returns and that low future growth of consumption implies low expected future returns, are characteristics shared by Campbell & Cochrane's model: the first effect because of habit formation and the second effect because of standard consumption smoothing.

4 Out-of-sample evidence

We believe that the in-sample predictive power of $G^{c,4}_t$ is striking. When viewed in the light of the Goyal & Welch (2008) findings, the out-of-sample results that we present in this section are perhaps even more striking, however. Goyal & Welsh (2008, page 1456) conclude that the models they investigate would not have helped "an investor who had sought to use these models for market-timing". In contrast, we now show that the fourth-quarter consumption change

[18] For instance, we implicitly assume that X_t includes last quarter's level of consumption only and that returns are linearly related to the surplus consumption ratio, whereas Campbell & Cochrane assume that habit is based on the whole history of consumption and nonlinearly related to returns.

predicts returns out-of-sample and that an investor who had used $G_t^{c,4}$ to predict returns would have gained in utility terms compared to a standard benchmark model.

There are two reasons why out-of-sample forecasts might be different from in-sample forecasts: The coefficients in the predictive model might not be stable over time and the consumption series available today might be different from the one available in real time due to data revisions. Where parameter instability is the usual concern in out-of-sample tests, the issue of data revisions is special to macroeconomic variables. Goyal & Welsh (2008) focus on stability of the predictive coefficients, as they mainly consider financial variables, and find that the models they analyze are not stable. Given that we consider a macroeconomic variable that is revised as time goes by, we proceed in two steps. First, we follow Lettau & Ludvigson (2001) and present out-of-sample statistics using the today-available revised measures of consumption. The use of the today-available revised figures in the out-of-sample analysis will illustrate how the in-sample results depend on the parameters estimated over the full sample, i.e. whether our in-sample results are robust towards the point of Goyal & Welsh (2008). As the use of today-available revised data is not representative for how a real-time investor could have performed because of data revisions, we show that our results are robust to using first-release data, as our second step.[19]

4.1 The procedure

Out-of-sample forecasting is based on a recursive scheme using all available data at the time of the forecast. We use the period from 1948 to 1974 as our starting period after which we make the out-of-sample forecasts. Our procedure is as follows: given an out-of-sample period from 1975 to 2007, we estimate the unrestricted forecasting model in Eq. (1) using data from 1948 to 1974 and make a forecast for 1975. Then, we re-estimate Eq. (1) using data from 1948 to 1975 and make a forecast for 1976. This procedure continues until the end of the sample in 2007. In a similar way, we generate out-of-sample forecasts using a restricted forecasting model with $\beta = 0$ in Eq. (1). Let $\hat{e}_{U,t+1} = R^e_{t+1} - \left(\hat{\alpha}_{U,t} + \hat{\beta}_{U,t} X_t\right)$ denote the forecast error using the unrestricted forecasting model in Eq. (1), and let $\hat{e}_{R,t+1} = R^e_{t+1} - \hat{\alpha}_{R,t}$ denote the forecast error using the restricted forecasting model with $\beta = 0$ in Eq. (1). The out-of-sample statistics

[19] Guo (2009) shows that it is important to check both the today-available revised measure of consumption and the real-time measure in out-of-sample investigations, as he finds that the out-of-sample performance of $\widehat{cay}$ depends upon the use of real-time consumption or revised consumption.

that we calculate are then given by:

$$ENC\text{-}NEW = \sum_{t=1}^{T} \Big(\hat{e}^2_{R,t+1}$$

the fourth quarter) to the end of the first quarter one year after, i.e. Q2-Q1 returns, when we use the $G^{c,4}$-variable to predict. For the benchmark variables (DP, TMS, $EQIS$, and $\widehat{cay}$), we want to compare with $G^{c,4}$, so we also predict the returns arising from the beginning of the second quarter and one year on when using these variables.[20] For the other consumption series, we predict one-year ahead returns starting after consumption data have been published, i.e. when using $G^{c,1}$, we predict returns during Q3-Q2, when $G^{c,2}$, we predict returns during Q4-Q3, and when $G^{c,3}$, we predict returns during the calendar year.

Certainty-equivalent gains. In order to provide a measure of the *economic* value of using $G^{c,4}$ to predict, we calculate the certainty-equivalent gains that a mean-variance investor would have obtained if this investor had used the fourth-quarter consumption growth rate (or another variable) to predict excess returns out-of-sample. For the mean-variance investor, the optimal portfolio weight in stocks is:

$$\omega_t = \frac{E_t\left(R^e_{t+1}\right)}{\gamma\sigma_t^2}, \tag{7}$$

where γ is the investor's relative risk aversion, σ_t^2 is the variance of the stock market, and $E_t\left(R^e_{t+1}\right)$ is the expected excess stock return based on the predictive regression in Eq. (1). For the unrestricted forecasting model, we calculate the optimal portfolio weight in stocks as $\omega_{U,t} = \frac{\hat{\alpha}_{U,t}+\hat{\beta}_{U,t}X_t}{\gamma\hat{\sigma}_t^2}$. For the restricted forecasting model with $\beta = 0$ in Eq. (1), the optimal portfolio weight in stocks is given by $\omega_{R,t} = \frac{\hat{\alpha}_{R,t}}{\gamma\hat{\sigma}_t^2}$. We calculate estimates of the variance of the stock market $\hat{\sigma}_t^2$ recursively using all available data for each period. We impose the portfolio constraints $0 \leq \omega_t \leq 150\%$, after which we calculate the portfolio return $R_{p,t} = \omega_t R_t + (1-\omega_t) R_{f,t}$. Finally, we calculate the certainty-equivalent return:

$$ce = E\left(R_p\right) - \frac{\gamma}{2} VAR\left(R_p\right). \tag{8}$$

We use $\gamma = 3$ in our calculations.

[20] We use the end-of-year values for the financial variables (DP and TMS) to predict Q2-Q1 returns. We have checked what happens if we use the end-of-first-quarter values of the financial variables to predict returns during the Q2-Q1 period. We found that there is not much difference between using end-of-year or end-of-first quarter values for DP and TMS when predicting returns during Q2-Q1 (results available upon request). In both cases, the benchmark variables do not predict returns particularly well. Given the persistence of the benchmark variables, it is not surprising that it is not too important whether we move them forward a quarter when predicting returns.

4.2 Results

Table 7 shows the results. We find that the only variable that generates $MSE_U/MSE_R < 1$, i.e. has a lower mean-squared forecast error than an updated historical mean (the restricted forecast) out-of-sample, and for which both of the tests for equal forecasts of the restricted and unrestricted models are strongly rejected, is the fourth-quarter consumption growth rate. The $G^{c,3}$-variable and $\widehat{cay}$ also yield $MSE_U/MSE_R < 1$, but the $ENC\text{-}NEW$ and $MSE\text{-}F$ tests cannot be rejected when using $G^{c,3}$ and the $MSE\text{-}F$ test cannot be rejected using $\widehat{cay}$. For the other variables, $MSE_U/MSE_R > 1$ and the $ENC\text{-}NEW$ and $MSE\text{-}F$ tests cannot be rejected implying that these variables predict significantly worse than an updated mean. In summary, the only variable that produces $MSE_U/MSE_R < 1$ and rejections of both the $ENC\text{-}NEW$ test and the $MSE\text{-}F$ test is $G^{c,4}$.

In Figure 3, we visualize the information contained in $G^{c,4}$ for returns out-of-sample. The figure shows the cumulated difference between the sum of squared forecast errors from the unrestricted and the restricted models. This cumulative difference is calculated as:

$$\text{Net-}SSE_T = \sum_{t=1975}^{T} \hat{e}_{R,t}^2 - \hat{e}_{U,t}^2.$$

Hence, if the cumulative difference is increasing over time, the restricted benchmark model has a higher mean squared error than the unrestricted model. As is relatively clear from the figure, only $G^{c,4}$ seems to produce a consistently lower mean squared error than the benchmark. For the commonly used predictors, the cumulative difference between the squared errors seems to be falling over time, indicating that these variables keep on predicting worse than the updated historical mean.

The R^2 from the models using the fourth-quarter consumption growth rate as a predictor is high: 14.81%. The R^2s from the models that use $G^{c,3}$ or $\widehat{cay}$ to predict are also positive, but not nearly as high as the one we find when we use $G^{c,4}$. Using other variables, we only find negative R^2s. We also notice that there is not a big difference between the constrained and the unconstrained R^2s. In other words, the predictions that $G^{c,4}$ delivers are generally "sensible" (in the sense of Campbell & Thompson), as a big difference between R^2 and R_c^2 would have implied that many out-of-sample forecasts would have been set to zero.

The certainty-equivalent return is 11.19% for the model using $G^{c,4}$ versus 8.29% for the

updated-mean model, i.e. the certainty-equivalent gain is 2.90% when using $G^{c,4}$ to predict compared to using the updated-mean model. This means that an investor would be willing to pay 2.90% of the invested wealth to get access to the information contained in $G^{c,4}$ compared to the situation where the investor had access to the information contained by the updated mean only. In this regard, the certainty-equivalent gain is sizeable. For $\widehat{cay}$, the certainty-equivalent gain is also positive, but not as high. For the other consumption growth rates, DP, and TMS, the gain is negative, meaning that an investor would have had a loss in utility if he had used these variables to make portfolio allocations, compared to using the updated historical mean.

4.3 Vintage data

Until now we have used the today-available revised figures for consumption. This is relevant when investigating the hypothesis that changes in consumption during the last quarter are related to expectations about next year's stock returns, as the revised consumption series is the one that best captures the actual consumption choices of consumers by taking into account all possible kinds of data revisions and improvements. An alternative question is whether a real-time market participant could have used the then-available consumption series to predict stock returns, i.e. whether one would gain from using the fourth-quarter consumption growth series to predict returns in real time. We turn to this question now.

A real-time practitioner who uses $G^{c,4}$ to improve his forecast of excess stock return faces two potentially important concerns. First, data from the Bureau of Economic Analysis are announced to the public with a delay of about one month. Second, data from the Bureau of Economic Analysis are subject to ongoing revisions. Advance, preliminary, and final estimates for the previous fourth quarter are typically released near the end of January, February, and March, respectively. In addition, annual revisions take place each summer, and comprehensive revisions take place at irregular intervals.

To examine the extent to which the out-of-sample predictive power of $G^{c,4}$ is sensitive to announcement delays and data revisions, we construct a real-time data set for $G^{c,4}$ based on vintage data from the ALFRED database at the Federal Reserve Bank of St. Louis. Our real-time data set consists of vintages spanning from March 1975 to March 2007, and the data observations from each vintage start in 1948. For instance, the March 1995 vintage contains data from 1948 to 1994. Each vintage incorporates the latest data revisions of $G^{c,4}$ (and the

other consumption growth rates). We assume that the real-time practitioner uses the final estimates of $G_t^{c,4}$ from each vintage $-$ available near the end of March $-$ to make his forecast of R_{t+1}^e, and, like in Section 4.2, measures the one-year ahead excess stock return from the beginning of the second quarter to the end of the first quarter next year. Since the ALFRED database does not provide vintage data for population numbers, we assume that the population growth is constant.

In Table 8, Panel A, we show the results from out-of-sample tests using vintage data. The point to stress from this table is that $G^{c,4}$ is also in real time a significant predictor of excess returns out-of-sample in both a statistical and economic sense. Statistically, Table 8 reveals that the null hypothesis of equal forecasting power is rejected using both the ENC-NEW and MSE-F tests, and $MSE_U/MSE_R < 1$. In an economic sense, the table shows that an investor would be willing to pay an annual fee of 1.20% of the invested wealth to get access to the real-time information contained in $G^{c,4}$. The out-of-sample R^2 of 5.61% is also higher than the OOS R^2 of any of the other variables used to predict returns out-of-sample, as can be seen by comparing Tables 7 and 8. In other words, even if using first-release data, the fourth-quarter consumption growth rate predicts returns better than any of the other commonly used predictors do. The latter point is a main finding of our paper.

In Panel B, we use the first-release of the fourth-quarter consumption growth rate, available in the end of January, to predict returns from the beginning of February to the end of January next year.[21] The results are shown in Panel B (we only show results for $G^{c,4}$; results using other quarters are available upon request). We find that even if using the very first data for consumption available in the end of January, the fourth-quarter consumption growth rate still predicts better than a random walk ($MSE_U/MSE_R < 1$). In additional, the OOS R^2 is 5.01%, the certainty-equivalent gain is 2.07%, and null-hypothesis of the MSE-F test is rejected, but the ENC-NEW test is not.

Comparing the results in Table 7 (that were generated using the today-available series for consumption) with those in Table 8 (that were generated using real-time data), it is seen that measurement errors in consumption makes the forecasts based on real-time data less precise

[21] For some reason, there is no 1995 $G^{c,4}$ observation in the 1996 vintage for January in the ALFRED database: That year, $G^{c,4}$ did not become available before February. To overcome this problem, we have assumed that the forecast made in February 1996 is equal to the historical average, i.e. in that single year, the restricted forecast is equal to the unrestricted forecast. It is also for this practical reason that we focus on the results using the March final numbers for consumption of each vintage in Panel A, Table 8.

compared to the "true" measure of consumption, as reflected in the today-available series that take into account data revisions and improvements. However, even when superior forecasts are made if using the "true" (but unfortunately not available in real time) consumption, it is a main point in the paper that even the real-time data for the fourth-quarter consumption growth rate still contain interesting information about expected returns, and, indeed, more precise information than in the other predictors commonly used in the literature.

4.4 Robustness of the out-of-sample tests

4.4.1 More variables

Goyal & Welch (2008) and Campbell & Thompson (2008) consider more variables than the benchmark variables that we have considered here. To make sure that we have not neglected some important predictive variables, we report the results from out-of-sample tests that use a host of other predictor variables in Table 9.[22] For all variables we measure the one-year ahead excess stock return from the beginning of the second quarter to the end of the first quarter next year.[23] The main result is that $G^{c,4}$ predicts significantly better than any other predictor. For instance, the out-of-sample R^2s are negative for all benchmark variables except for the consumption-wealth ratio and the default return spread that produce out-of-sample R^2s of 2.78% and 2.96%, respectively, whereas the fourth-quarter consumption growth rate produces an out-of-sample R^2 of 14.81%. Except for the consumption-wealth ratio, the in-sample R^2 of the fourth-quarter consumption growth rate is also much higher than that arising from the use of any other predictor.

4.4.2 A shorter out-of-sample forecasting period.

Ang & Bekaert (2007) find that predictability by the dividend yield breaks down when including the 1990s in the sample. Above, we have shown that $G^{c,4}$ predicts returns out-of-sample during the 1975-2007 period, i.e. including the post-1990 period. Nevertheless, we conducted our

[22] For a description of these variables, their data sources, and construction, please refer to Goyal & Welch (2008). All in all, we have followed Goyal & Welch (2008) closely when constructing these variables.

[23] Like in Tables 7 and 8, we use also here end-of-year values of all predictor variables. We have checked what happens if we use end-of-first-quarter values of the financial predictor variables. We find that the results are not changed qualitatively. The only notable change, compared to the numbers shown in Table 9, is that the default return spread gets a negative OOS R^2 of -17.13%, whereas the stock variance turns out to be a slightly better predictor than a constant with an OOS R^2 of 0.51%.

out-of-sample investigation over a post-1990 period. The results are in Table 10 where Panel A shows results using the today-available revised series for consumption, Panel B shows results using real-time vintage data available in the end of March each year, and Panel C shows how the benchmark variables normally used in the literature performed during the short post-1990 period.

The overall result is that the fourth-quarter consumption growth rate still predicts better than the updated historical mean, and better than any of the variables with which we compare it. It could seem that $\widehat{cay}$ predicts more precisely than $G^{c,4}$ based on real-time data (comparing results for $G^{c,4}$ in Panel B with those using $\widehat{cay}$ in Panel C, shows that the R^2 is slightly bigger using $\widehat{cay}$, for instance). It must be remembered, though, that $\widehat{cay}$ is based on today-available consumption (i.e. the performance of $\widehat{cay}$ should be compared with the numbers in Panel A of Table 10), and suffers from a potential look-ahead bias as it is based on estimated cointegration parameters. Hence, the fourth-quarter consumption growth rate is the only variable that predicts better in real time than the updated historical mean ($R^2 = 2.80\%$) during the 1990s. The fact that the forecasts from $G^{c,4}$ are not statistically different from those of an updated historical mean is most likely due to a low power of the tests in the short out-of-sample sample period used here.

Even when $G^{c,4}$ predicts better than the other variables and the updated historical mean, we do at the same time confirm Ang & Bekaert's (2007) findings that it is more difficult to predict during the post-1990 period (MSE_U/MSE_R is lower in Table 7 than in Table 10, the R^2 is higher in Table 7 than in Table 10, etc.).

5 Predictions of the equity premium during the financial crisis of 2008-2009

2008 saw the most severe stock market decline since the Great Depression. The year after, 2009, saw a remarkable turnaround with high returns. Given these outstanding movements in the equity premium, we found it interesting to reserve the financial crisis of 2008-2009 as a "case-study" that we can use to scrutinize the stability and out-of-sample forecasting performance of the fourth-quarter consumption growth rate. We believe this gives interesting additional insights into the explanatory power of the fourth-quarter consumption growth rate, compared

to having included 2008 and 2009 into the general analysis.

Table 11 presents recursive estimates starting with the 1948-2004 period, and successively adding one more year (starting the recursive scheme earlier than 2004 does no change the picture). We first note the consistency with which the fourth-quarter consumption growth rate predicts returns up until the crisis: Choosing 2004, 2005, 2006, or 2007, one gets very stable estimates. When adding 2008, the R^2 and t-statistic drop, but then increase again when adding 2009, indicating that the fourth-quarter consumption growth rate did not predict the stock market crash in 2008, but captured 2009 well. To compare with standard predictor variables, it can be mentioned that the R^2 from predicting with the dividend yield until 2009 increases to 10.59%, from the 9.13% shown in Table 2. This is an exemplification of the findings in Section 3.2.5 that the dividend yield generally performs better during recessions. On the other hand, the forecasting performance of $\widehat{cay}$ drops when expanding the sample until 2009: The R^2 is reduced to 11.48% (from 15.09% in Table 2). The R^2 from the bivariate model using $G^{c,4}$ and $\widehat{cay}$ to predict is 22.11%, i.e. the R^2 increases a lot compared to univariate case where only $\widehat{cay}$ is used, but not so much compared to the univariate case where $G^{c,4}$ is used on its own. In other words, even when including the crisis of 2008-2009, the fourth-quarter consumption growth rate predicts better than the dividend yield and $\widehat{cay}$ that are often used as predictor variables in the literature, and the general conclusions regarding the strong performance of $G^{c,4}$ compared to standard predictor variables hold also after including 2008-2009.

The fourth-quarter consumption growth rate predicted the following equity premiums for 2008 and 2009 (with 95% confidence intervals in brackets):[24]

$$
\begin{array}{lll}
\text{2008:} & 0.17 - 4.20 \cdot 0.01\% = 16.71\% & [-13.24\%; 46.66\%] \\
\text{2009:} & 0.15 - 3.72 \cdot (-3.21\%) = 26.74\% & [-6.23\%; 59.70\%]
\end{array}
$$

Using the updated mean, the forecast would had been 7.78% [−25.47%; 41.03%] for 2008 and 6.98% [−26.20%; 39.75%] for 2009.

These results show that the fourth-quarter consumption growth rate predicted a positive risk premium for 2008, implying that it could not foresee the largest drop in the equity premium during the sample period of 40.36%. The −40.36% was even outside the confidence intervals.

[24] The standard deviation of the forecast error from the forecasting regression using data for the whole period up until 2008 (2009) is 15.28% (16.82%) using $G^{c,4}$ and 16.96% (16.82%) using the updated mean. Hence, the conference intervals around the forecasts are large, and are even larger using the updated mean.

In hindsight, this is probably not surprising: The financial crisis was a massive outlier in all aspects, and the fourth-quarter consumption growth rate could not, like any of the other well-known stock return predictors used in the literature, forecast it. On the other hand, the drop in consumption during the last quarter of 2008 (-3.21% change in real per capita consumption) implied that the forecast for 2009 was very close indeed to the realized equity premium (a forecast of 26.74% versus the actually observed 26.63%), and the model did considerably better than the updated mean model.

6 Conclusion

Goyal & Welsh (2008) find that it is difficult to identify variables that consistently predict annual excess returns better than a random walk out-of-sample. In this paper, we have shown that the fourth-quarter consumption growth rate is one such variable. It is interesting that a not-estimated pure macroeconomic variable predicts annual excess returns in-sample and out-of-sample, even in real time, as it links movements in expected returns tightly to a pure business cycle variable. It is also sensible that it is exactly the fourth quarter of the year that predicts returns, as special attention is devoted to consumption (the "Christmas demand shock") and investments (due to resolution of different uncertainties) during the fourth quarter.

Due to the nature of the construction of the fourth-quarter consumption growth rate, it obviously cannot be used to predict returns at other points of time during the year. Hence, a financial market participant who wants to gauge the expected one-year return as of, say, the third quarter of the year cannot use the predictor that we analyze in this paper. In this sense, there is a limitation to the practical use of the fourth-quarter consumption growth rate. However, for the overall question of whether excess returns are predictable at all, or for the question of what next year's excess return will be, the fourth-quarter consumption growth rate seems to contain interesting information.

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Table 1. Summary statistics.

	Consumption growth rates				Benchmark predictive variables			
	$G^{c,1}$	$G^{c,2}$	$G^{c,3}$	$G^{c,4}$	DP	TMS	$EQIS$	$\widehat{cay}$
	Univariate statistics							
Mean	2.06%	2.26%	1.98%	2.11%	0.03	0.01	0.19	0.00
SD	1.95%	1.90%	1.84%	2.06%	0.01	0.02	0.08	0.02
Min	−3.15%	−4.50%	−3.72%	−3.44%	0.01	−0.04	0.05	−0.04
Max	6.74%	6.61%	4.92%	8.34%	0.07	0.04	0.43	0.04
AC	0.02	−0.11	0.11	0.01	0.90	0.53	0.70	0.71
	Correlation matrix							
$G^{c,1}$	1.00	0.24	0.41	0.24	−0.10	−0.05	0.11	−0.29
$G^{c,2}$		1.00	0.28	0.12	−0.00	0.09	0.06	−0.14
$G^{c,3}$			1.00	0.30	−0.15	−0.06	0.05	−0.31
$G^{c,4}$				1.00	−0.21	−0.03	0.19	−0.27
DP					1.00	−0.20	0.44	0.25
TMS						1.00	−0.18	0.35
$EQIS$							1.00	−0.20
$\widehat{cay}$								1.00

The table reports summary statistics of quarterly real per capita consumption growth rates and benchmark predictive variables. We have multiplied the consumption growth rates with 4, such that the quarterly consumption growth rates are expressed as percentage points per year.

Table 2. In-sample predictive regressions of one-year ahead excess stock returns.

	Consumption growth rates				Benchmark predictive variables			
	$G^{c,1}$	$G^{c,2}$	$G^{c,3}$	$G^{c,4}$	DP	TMS	$EQIS$	$\widehat{cay}$
β	−0.27	−1.57	−1.73	−4.20	4.36	1.72	−0.53	4.08
t-value	−0.28	−1.82	**−2.10**	**−5.68**	**2.74**	1.52	**−2.03**	**3.85**
$\bar{R}^2$	−1.65%	1.18%	1.14%	22.91%	9.13%	0.40%	4.50%	15.09%
	Bivariate regression with $G^{c,4}$ and $\widehat{cay}$							
β				−3.54				3.02
t-value				**−4.04**				**2.39**
$\bar{R}^2$								30.30%

The table reports results of in-sample predictive regressions of one-year ahead excess stock returns on the lag of predictive variables. For $G^{c,1}$, the one-year ahead excess stock return is measured from the beginning of the second quarter to the end of the first quarter next year. For $G^{c,2}$, the one-year ahead excess stock return is measured from the beginning of the third quarter to the end of the second quarter next year. For $G^{c,3}$, the one-year ahead excess stock return is measured from the beginning of the fourth quarter to the end of the third quarter next year. For $G^{c,4}$, DP, TMS, $EQIS$, and $\widehat{cay}$, the one-year ahead excess stock return is measured over the calendar year. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic.

Table 3. In-sample predictive regressions of calendar quarter excess stock returns.

		Calendar quarter return			
		Q1	Q2	Q3	Q4
$G^{c,1}$	β	−0.67	0.21	0.92	−0.73
	t-value	−1.11	0.52	1.30	**−1.97**
	$\bar{R}^2$	1.21%	−1.46%	2.51%	1.92%
$G^{c,2}$	β	−0.16	−0.77	−0.51	0.04
	t-value	−0.35	−1.80	−1.05	0.09
	$\bar{R}^2$	−1.59%	1.87%	−0.54%	−1.74%
$G^{c,3}$	β	−0.56	−0.03	−0.77	−0.19
	t-value	−1.25	−0.07	−1.70	−0.68
	$\bar{R}^2$	0.09%	−1.75%	0.92%	−1.54%
$G^{c,4}$	β	−1.00	−0.83	−0.78	−1.13
	t-value	**−2.50**	**−1.98**	−1.23	**−2.50**
	$\bar{R}^2$	5.55%	3.26%	1.69%	7.80%

The table reports results of in-sample predictive regressions of calendar quarter excess stock returns on the lag of quarterly consumption growth rates. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic.

Table 4. In-sample predictive regressions of multi-period ahead excess stock returns.

		Forecast horizon k							
		1	2	3	4	8	12	16	20
$G^{c,1}$	β	0.21	1.04	0.28	−0.27	−1.49	−3.98	−3.92	−4.51
	t-value	0.52	1.08	0.27	−0.28	−1.35	**−2.64**	−1.78	−1.25
	$\bar{R}^2$	−1.46	1.15	−1.60	−1.65	−0.30	3.61	1.50	0.95
$G^{c,2}$	β	−0.51	−0.52	−0.73	−1.57	−0.62	−2.49	−3.33	−3.57
	t-value	−1.05	−0.79	−1.03	−1.82	−0.31	−1.36	−1.45	−1.08
	$\bar{R}^2$	−0.54	−0.98	−0.76	1.18	−1.57	0.12	0.35	−0.40
$G^{c,3}$	β	−0.19	−0.77	−0.82	−1.73	−4.87	−4.91	−3.83	−8.76
	t-value	−0.68	−1.39	−1.06	**−2.10**	**−2.83**	**−3.08**	−1.57	**−2.95**
	$\bar{R}^2$	−1.54	−0.39	−0.89	1.14	8.58	5.28	1.21	7.13
$G^{c,4}$	β	−1.00	−1.88	−2.77	−4.20	−6.32	−5.14	−6.93	−12.33
	t-value	**−2.50**	**−2.67**	**−3.85**	**−5.68**	**−4.43**	**−2.91**	**−4.74**	**−7.30**
	$\bar{R}^2$	5.55	8.30	11.67	22.91	22.66	8.94	10.77	21.66

The table reports results of in-sample predictive regressions of k-period ahead excess stock returns on the lag of quarterly consumption growth rates, where k denotes the forecast horizon in quarters. For $G^{c,1}$, the forecast horizon is measured from the second quarter and k periods ahead. For $G^{c,2}$, the forecast horizon is measured from the third quarter and k periods ahead. For $G^{c,3}$, the forecast horizon is measured from the fourth quarter and k periods ahead. For $G^{c,4}$, the forecast horizon is measured from the first quarter and k periods ahead. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic (in %).

Table 5. Vector autoregression and impulse response functions.

	Dependent variable			
	r_{t+1}	Δd_{t+1}	dp_{t+1}	$G^{c,4}_{t+1}$
r_t	0.06	0.05	−0.01	0.02
	(0.12)	(0.05)	(0.12)	(0.02)
Δd_t	0.23	0.26	0.04	−0.01
	(0.32)	(0.13)	(0.33)	(0.05)
dp_t	0.08	0.00	0.95	−0.00
	(0.04)	(0.02)	(0.04)	(0.01)
$G^{c,4}_t$	−3.29	0.21	3.55	−0.04
	(0.92)	(0.38)	(0.94)	(0.14)
	Effect of a one unit $G^{c,4}$ innovation			
Period	r_{t+1}	Δd_{t+1}	dp_{t+1}	$G^{c,4}_{t+1}$
1	0	0	0	1
2	−3.29	0.21	3.55	−0.04
	(0.92)	(0.38)	(0.94)	(0.14)
3	0.30	−0.10	3.25	−0.08
	(0.63)	(0.23)	(1.04)	(0.07)
4	0.52	−0.02	2.79	0.00
	(0.33)	(0.09)	(0.91)	(0.03)
5	0.26	0.03	2.64	0.00
	(0.19)	(0.08)	(0.86)	(0.02)
6	0.24	0.03	2.51	−0.00
	(0.13)	(0.07)	(0.86)	(0.02)
7	0.24	0.02	2.37	−0.00
	(0.11)	(0.07)	(0.87)	(0.02)
8	0.23	0.02	2.23	−0.00
	(0.10)	(0.07)	(0.88)	(0.02)
9	0.21	0.02	2.10	−0.00
	(0.09)	(0.06)	(0.90)	(0.01)
10	0.20	0.02	1.98	−0.00
	(0.08)	(0.06)	(0.91)	(0.01)

The table reports vector autoregression estimates and impulse response functions of a one unit shock to $G^{c,4}_{t+1}$. Standard errors are in parentheses.

Table 6. In-sample predictive regressions of one-year ahead excess stock returns on quarterly growth rates of GDP, final sales, and retail sales.

	G^1	G^2	G^3	G^4
		GDP		
β	−2.90	−2.42	2.40	−7.25
t-value	−0.97	−1.15	0.75	**−4.53**
$\bar{R}^2$	2.63%	0.03%	−0.63%	15.68%
		Final sales		
β	−2.52	−0.74	−1.32	−6.52
t-value	−1.03	−0.37	−0.45	**−4.22**
$\bar{R}^2$	−0.00%	−1.61%	−1.41%	9.10%
		Retail sales		
β	0.14	0.10	0.66	−2.70
t-value	0.13	0.10	0.42	**−3.92**
$\bar{R}^2$	−1.73	−1.72	−1.49%	8.01%

The table reports results from in-sample predictive regressions of one-year ahead excess stock returns on the lag of predictive variables. The predictive variables are the quarterly growth rates of seasonally adjusted real GDP, real final sales, and real retail sales of food and services. For G^1, the one-year ahead excess stock return is measured from the beginning of the second quarter to the end of the first quarter next year. For G^2, the one-year ahead excess stock return is measured from the beginning of the third quarter to the end of the second quarter next year. For G^3, the one-year ahead excess stock return is measured from the beginning of the fourth quarter to the end of the third quarter next year. For G^4, he one-year ahead excess stock return is measured over the calendar year. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic.

Table 7. Out-of-sample predictability of one-year ahead excess stock returns relative to the historical mean.

	$\frac{MSE_U}{MSE_R}$	$ENC\text{-}NEW$	$MSE\text{-}F$	R^2	R^2_C	Δce
$G^{c,4}$	0.85	4.36*	5.74*	14.81	14.74	2.90
$G^{c,1}$	1.07	−0.44	−2.24	−7.28	−7.28	−1.18
$G^{c,2}$	1.04	−0.63	−1.41	−4.47	−4.47	−0.63
$G^{c,3}$	0.98	1.29	0.78	2.30	2.18	−0.16
DP	1.12	1.13	−3.39	−11.44	−2.56	−1.54
TMS	1.12	−1.07	−3.47	−11.75	−11.75	−1.55
$EQIS$	1.13	−0.63	−3.82	−13.11	−4.61	0.02
$\widehat{cay}$	0.97	4.58*	0.98	2.89	0.82	2.08

$ENC\text{-}NEW$ is the forecast encompassing test of Clark & McCracken (2001). $MSE\text{-}F$ is the equal forecast accuracy test of McCracken (2004). Asymptotic critical values at the 5% significance level are 1.72 for the $ENC\text{-}NEW$ test and 1.58 for the $MSE\text{-}F$ test. We indicate with "*" a significant test statistics. R^2 is the unconstrained Campbell & Thompson (2008) out-of-sample R^2-statistic. R^2_C imposes the constraint that negative out-of-sample forecasts are replaced with zeros. Δce is the certainty-equivalent gain. The utility function is $E(R_p) - \frac{\gamma}{2} VAR(R_p)$ with a risk aversion of $\gamma = 3$. The optimal portfolio weight in stocks is constrained at $0 \leq \omega_t \leq 150\%$. For $G^{c,1}$, the one-year ahead excess stock return is measured from the beginning of the third quarter to the end of the second quarter next year. For $G^{c,2}$, the one-year ahead excess stock return is measured from the beginning of the fourth quarter to the end of the third quarter next year. For $G^{c,3}$, the one-year ahead excess stock return is measured over the calendar year. For $G^{c,4}$, DP, TMS, $EQIS$, and $\widehat{cay}$, the one-year ahead excess stock return is measured from the beginning of the second quarter to the end of the first quarter next year.

Table 8. Out-of-sample predictability of one-year ahead excess stock returns using vintage data: Tests and explanatory power.

	$\frac{MSE_U}{MSE_R}$	$ENC\text{-}NEW$	$MSE\text{-}F$	R^2	R^2_C	Δce
		A. Using final estimates released in March				
$G^{c,1}$	1.00	0.42	−0.02	−0.06	−0.06	−0.02
$G^{c,2}$	1.00	0.03	−0.06	0.19	0.19	−0.12
$G^{c,3}$	1.00	0.76	−0.12	−0.37	−0.37	−0.12
$G^{c,4}$	0.94	1.93*	1.99*	5.61	6.16	1.20
		B: Using first-release estimates released in January				
$G^{c,4}$	0.95	1.28	1.74*	5.01	5.01	2.07

The quarterly consumption growth rates are measured based upon vintage data. In Panel A, we use the estimate from each vintage of $G^{c,4}$ available in the end of March. In Panel A, the timing of returns is as explained in the notes to Table 7. In Panel B, we use the first-release estimate of $G^{c,4}$ available in the end of January. In this case, the one-year ahead excess stock return is measured from the beginning of February to the end of January next year. We indicate with "*" a significant test statistics. Otherwise see notes to Table 7.

Table 9. Out-of-sample predictability of one-year ahead excess stock returns: More variables.

		IS t-value	IS R^2	OOS R^2	MSE-F
$G^{c,4}$	4th q. consumption growth	−3.95	15.62	14.81	5.74*
DP	Dividend-price ratio	2.63	8.82	−11.44	−3.39
DY	Dividend yield	1.76	3.32	−13.80	−4.00
EP	Earnings-price ratio	2.83	7.23	−3.50	−1.11
DE	Dividend-payout ratio	0.18	−1.71	−10.04	−3.01
$SVAR$	Stock variance	−0.05	−1.75	−5.46	−1.71
BM	Book-to-market	1.15	0.68	−13.73	−3.98
$NTIS$	Net equity expansion	−0.10	−1.74	−4.09	−1.30
$EQIS$	Pct equity issuing	−0.75	−0.96	−13.11	−3.82
TBL	T-bill rate	−1.65	1.23	−28.29	−7.28
LTY	Long-term yield	−0.93	−0.60	−34.85	−8.53
LTR	Long-term return	0.59	−1.34	−8.03	−2.45
TMS	Term spread	1.24	0.17	−11.75	−3.47
DFY	Default yield spread	−0.20	−1.71	−9.86	−2.96
DFR	Default return spread	−2.17	3.34	2.96	1.01
$INFL$	Inflation	−0.73	−1.15	−22.32	−6.02
IK	Investment-capital ratio	−1.57	2.11	−12.39	−3.64
$\widehat{cay}$	Consumption-wealth ratio	4.44	17.34	2.89	0.98

Table 10. Out-of-sample predictability during the 1990-2007 period.

	$\frac{MSE_U}{MSE_R}$	$ENC\text{-}NEW$	$MSE\text{-}F$	R^2	R_C^2	Δce
		A. Today-available data				
$G^{c,1}$	1.10	−0.58	−1.59	−9.67	−9.67	−0.45
$G^{c,2}$	1.01	−0.08	−0.16	−0.87	−0.87	−0.21
$G^{c,3}$	0.99	0.36	0.14	0.76	0.76	−0.64
$G^{c,4}$	0.89	1.88*	2.13*	10.59	10.59	3.82
		B. Real-time data				
$G^{c,1}$	1.02	−0.12	−0.42	−2.39	−2.39	−0.04
$G^{c,2}$	1.00	0.01	−0.01	−0.08	−0.08	−0.20
$G^{c,3}$	0.98	0.51	0.43	2.34	2.34	−0.18
$G^{c,4}$	0.97	0.60	0.52	2.80	2.80	1.53
		C. Benchmark variables				
DP	1.29	−0.13	−4.08	−29.36	−13.65	−1.55
TMS	1.04	−0.13	−0.72	−4.14	−4.14	−1.21
$EQIS$	1.09	−0.41	−1.42	−8.60	−8.60	−1.25
$\widehat{cay}$	0.96	3.15*	0.71	3.77	0.12	1.67

$ENC\text{-}NEW$ is the forecast encompassing test of Clark & McCracken (2001). $MSE\text{-}F$ is the equal forecast accuracy test of McCracken (2004). Asymptotic critical values at the 5% significance level are 1.08 for the $ENC\text{-}NEW$ test and 1.30 for the $MSE\text{-}F$ test. We indicate with "*" a significant test statistics. Otherwise see notes to Table 7.

Table 11. Recursive predictive regressions of one-year ahead excess stock returns.

	2004	2005	2006	2007	2008	2009
β	-4.19	-4.19	-4.19	-4.20	-3.72	-3.72
t-value	$\mathbf{-5.67}$	$\mathbf{-5.68}$	$\mathbf{-5.67}$	$\mathbf{-5.68}$	$\mathbf{-4.42}$	$\mathbf{-5.01}$
$\bar{R}^2$	22.77%	22.85%	22.84%	22.91%	15.77%	17.35%

The table reports results of predictive regressions of one-year (calendar year) ahead excess stock returns on the lag of the fourth quarter consumption growth rate for different samples starting in 1948 and ending in the year showed in the first row of the table. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic.

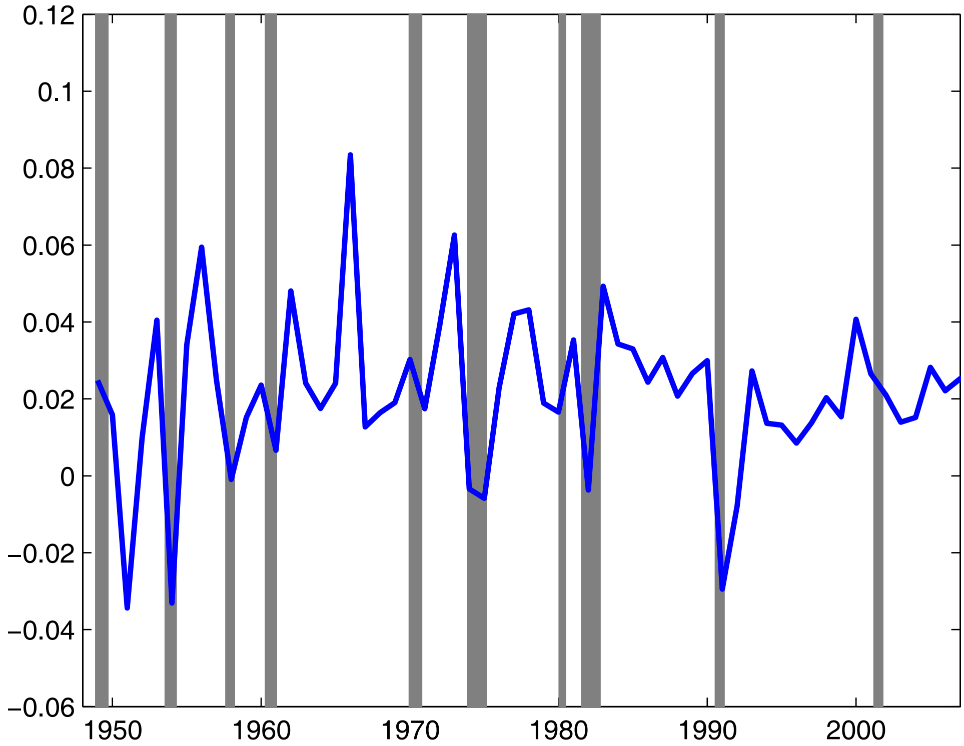

Figure 1. The fourth-quarter consumption growth rate and NBER recessions.

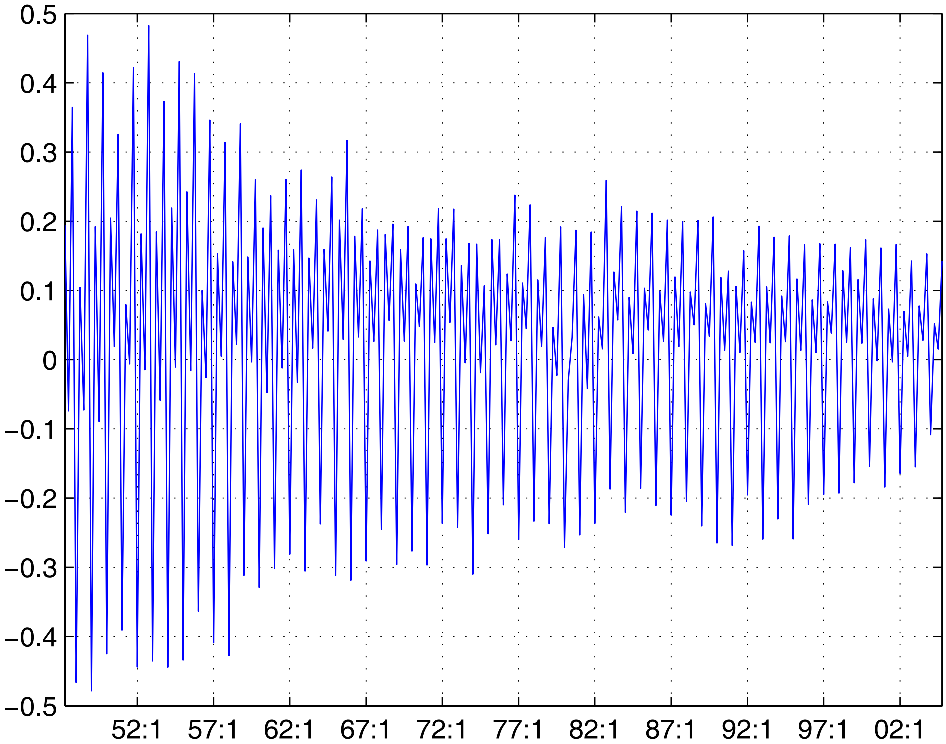

Figure 2: Annualized quarterly growth rates of no-seasonally adjusted consumption.

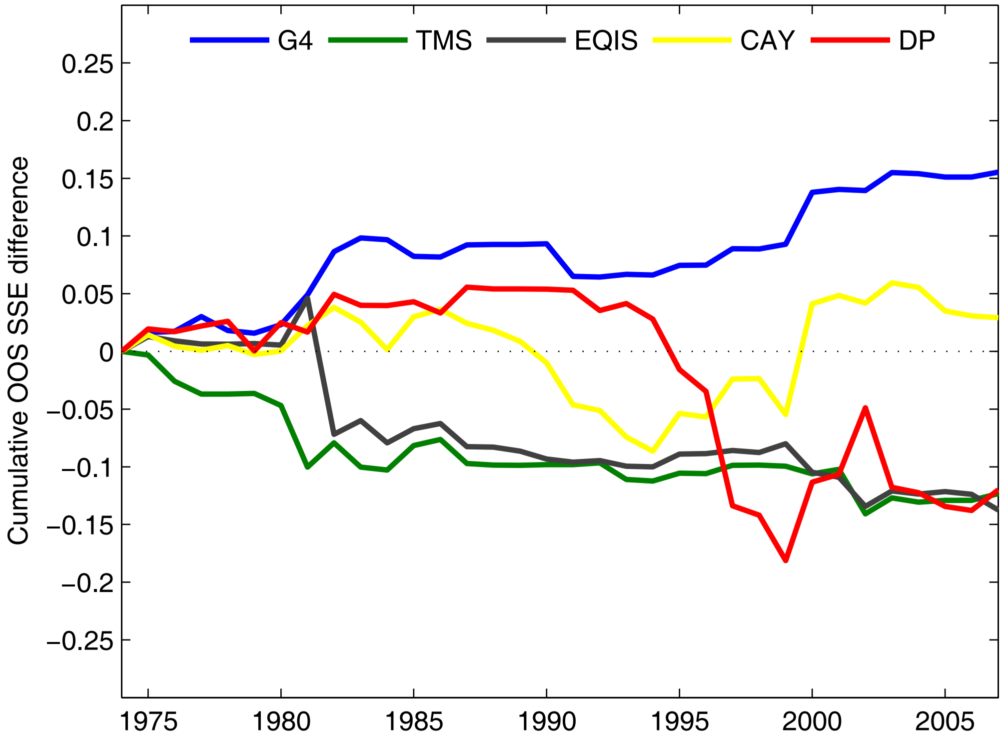

Figure 3. Out-of-sample predictability of one-year ahead excess stock returns: Cumulative sum of squared forecast errors. The figure shows the cumulative SSE difference from forecasting one-year ahead excess stock returns using a predictive variable relative to the historical mean. The cumulative SSE difference is calculated as:

$$\text{Net-}SSE_T = \sum_{t=1975}^{T} \hat{e}^2_{R,t} - \hat{e}^2_{U,t},$$

where $\hat{e}_{R,t}$ is the forecast error based on the historical mean (restricted forecasting model), and $\hat{e}_{U,t}$ is the forecast error based on the predictive variable (unrestricted forecasting model).