End-of-the-year economic growth and time-varying expected returns

Stig V. Møller and Jesper Rangvid

CREATES Research Paper 2012-42

Department of Economics and Business
Aarhus University
Fuglesangs Allé 4
DK-8210 Aarhus V
Denmark

Email: oekonomi@au.dk
Tel: +45 8716 5515

End-of-the-year economic growth and time-varying expected returns*

Stig V. Møller† Jesper Rangvid‡

Abstract

We show that macroeconomic growth at the end of the year (fourth-quarter or December) strongly predicts the returns of the aggregate market, small- and large-cap stocks, portfolios sorted on book-to-market and dividend yields, bond returns, and international stock returns, whereas economic growth during the rest of the year does not predict returns. End-of-the-year economic growth rates contain considerably more information about expected returns than standard variables used to predict returns, are robust to the choice of macro variables, and work in-sample, out-of-sample, and in subsamples. To explain these results, we show as the second main finding of our paper that economic growth and growth in economic confidence (consumer confidence and business confidence) are strongly correlated during the fourth quarter, but not during the other quarters. In summary, we therefore show that when economic growth is low at the end of the year, confidence in the economy is also low such that investors require higher future returns. During the rest of the year, there are no such relations between growth, confidence, and returns.

Keywords: End-of-the-year (fourth-quarter) economic growth, expected returns, consumer confidence, purchasing managers index, risk compensation.

JEL codes: E44; G12; G14

*We thank Caio Almeida (WFA discussant), Geert Bekaert, Lasse Bork, Peter Christoffersen, John Cochrane, Hui Guo, Søren Hvidkjær, Ralph Koijen (CEPR ESSFM discussant), Lasse Pedersen, Maik Schmeling, Andreas Schrimpf, Annette Vissing-Jørgensen, Jan Wrampelmeyer (EFA discussant), and participants at many seminars and conferences for comments and suggestions. The paper includes some results from an early paper entitled "The fourth-quarter consumption growth rate: A pure-macro, not-estimated stock return predictor that works in-sample and out-of-sample". Møller acknowledges support from CREATES, funded by the Danish National Research Foundation.

†CREATES and Department of Economics and Business, Aarhus University, Fuglesangs Allé 4, 8210 Aarhus, Denmark. Phone: (45) 8948 6188 and e-mail: svm@asb.dk.

‡Department of Finance, Copenhagen Business School, Solbjerg Plads 3, 2000 Frederiksberg, Denmark. Phone: (45) 3815 3615 and e-mail: jr.fi@cbs.dk.

1 Introduction

Understanding the interplay between expected returns and the macroeconomy is crucial for understanding the fundamental underlying determinants of asset prices and expected returns (Cochrane, 2007 and Ludvigson, 2011). Our contribution in this paper is to document and explain an intriguing result: Movements in macroeconomic growth rates during certain times of the year contain much more information about the time variation in expected returns than movements during other times of the year. Specifically, we show that growth in seasonally adjusted macroeconomic variables (real consumption, real GDP, industrial production, employment, capacity utilization, real labor income, etc.) between the third and the fourth quarter of a year contains a surprisingly large amount of information about expected excess returns over the next year from bonds and stocks, in-sample and out-of-sample, and in the U.S. as well as internationally. Economic growth during the other quarters does not predict returns. We find that low fourth-quarter macroeconomic growth predicts high future returns.

What can explain these findings? We show as the second main finding of our paper that economic growth is strongly correlated with growth in economic confidence (consumer confidence and business confidence) at the end of the year, but not during the first three quarters of the year. Low (high) economic growth at the end of the year thus goes hand-in-hand with lower (higher) confidence in the economy at the end of the year making investors require higher (lower) returns. During the rest of the year there is no such effect, and economic growth during the other quarters does not predict returns.

In more detail, we start out documenting thoroughly that end-of-the-year macroeconomic growth rates capture time-series movements in expected returns very strongly. We show that the R^2s from regressing one-year-ahead excess stock returns on the fourth-quarter growth rate of, e.g., real GDP, real consumption, or industrial production are 15%, 16%, and 18%, respectively, which can be compared to the 11% or so that are generated by the typical variables used in the literature to predict returns, such as the dividend-price ratio or the $\widehat{cay}$ ratio of Lettau & Ludvigson (2001). We also show, and this is the key point in the paper, that the growth rates of macroeconomic variables during the other quarters of the year are not significant predictors of excess returns. This explains why macroeconomic growth rates in general have been thought to contain only little information about expected returns:[1] The strong information contained by the fourth quarter is difficult to detect from a typical time-series regression of future returns on macroeconomic growth rates using all quarters as, in such a regression, the significant fourth-quarter effect gets mixed up with the effects from the other quarters that do not contain information about expected returns.

We show that these results extend to many other settings than the U.S. in-sample equity return situation. For instance, we study out-of-sample predictability. Goyal & Welch (2008) show that traditional variables work poorly out-of-sample in that they generate low or negative out-of-sample R^2s. We confirm this. Fourth-quarter economic growth rates, on the other hand, are significant predictors of excess returns out-of-sample with R^2s around 10%, even when using vintage data available to the investor in real time. We also find that fourth-quarter macroeconomic growth rates predict bond returns, and, again, only the fourth-quarter economic growth rate contains this information; economic growth during the other quarters does not. In addition, fourth-quarter economic growth rates predict returns on both large-cap and small-cap stocks, stocks sorted on book-to-market values and dividend yields. We also show that fourth-quarter growth rates predict returns, in particular on small-cap stocks, even if we concentrate on the post-1980 subsample; a period during which standard predictor variables have difficulties forecasting returns as Goyal & Welsh (2008) show. We focus on quarterly observations in our paper as most macrovariables are quarterly. Using monthly observations on industrial production, we show that within the fourth quarter, December growth rates capture a higher fraction of variation in expected returns than November and October growth rates. Finally, the fourth-quarter growth rate of industrial production in the G-7 countries is a strong predictor of excess returns on the world market portfolio as well as on regional portfolios, such as the European portfolio, the EAFE portfolio (Europe, Australia, Far East), and so on, whereas growth rates during the other quarters do not predict returns globally, i.e., noteworthy, this is

[1] Lettau & Ludvigson (2010, page 625) write: "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."

not just a U.S. phenomenon.

In order to explain these results, we show that there is a link between macroeconomic developments during the fourth quarter and confidence during the fourth quarter. We investigate two measures of confidence: Consumer confidence and business confidence. We find that macroeconomic growth rates and growth rates in confidence are strongly significantly correlated (positively) during the fourth quarter but not, or only marginally, correlated during other quarters. This means that when economic activity is low (high) at the end of the year, consumer and business confidence is also low (high) at the end of the year. During the rest of the year there is no such relation. This helps us understand our findings: Fourth quarters with low growth generate high future returns as confidence in the economy tends to be low during such periods and required returns correspondingly high. This implies, as we find, a negative coefficient in a regression of future excess returns on end-of-the-year economic growth. These effects do not arise during the other quarters, and there is no significant return predictability by macroeconomic growth rates during the other quarters. We confirm this intuition by showing that growth in confidence at the end of the year is a stronger predictor of returns than confidence during the rest of the year.

We illustrate most of our results using real GDP, real consumption, and industrial production. We show, though, that our overall finding that fourth-quarter, and only fourth quarter, economic activity predicts returns and that economic activity and consumer confidence are positively correlated during the fourth quarter, and only during the fourth quarter, is something that characterizes many macroeconomic variables, such as the output gap, the investment-capital ratio of Cochrane (1991), the housing-collateral ratio of Lustig & van Nieuwerburgh (2005), nonfarm employment growth, labor income growth, changes in the capacity utilization rate (total industry), nonresidential investment growth, changes in civilian unemployment rate, changes in average weekly hours in manufacturing, changes in overtime hours, etc.

Our results are consistent with an explanation that relies on a rational relation between time-varying economic growth, confidence, risk aversion, and expected returns: Economic growth at the end of the year predict returns because investors feel less confident when the economy is doing bad at the end of the year. This increases their aversion against taking on financial risk, and thereby pushes up required returns. During the rest of the year, there is no such relation. There is an alternative, perhaps more behavioral, interpretation of our results, however, that we also briefly discuss. If confidence is related to investor sentiments, periods where consumers and firms are optimistic could be periods where investors bid up asset prices above their fundamental values. Given that prices eventually will revert to their fundamental values, positive changes in confidence will predict low future returns. This is the mispricing explanation investigated in Brown & Cliff (2005), Qui & Welch (2006), Baker & Wurgler (2006), and Schmeling (2009). Brown & Cliff (2005) and Baker & Wurgler (2006) argue that optimism-based mispricing should be stronger for stocks that are harder to arbitrage, such as small stocks, growth stocks, and non-dividend paying stocks. We find that small stocks are indeed more predictable by fourth-quarter economic growth than large-cap stocks. Results for dividend-sorted and book-to-market sorted portfolios do not support the mispricing hypothesis, however, as hard-to-arbitrage stocks are found to be as predictable, but not more, than other kinds of stocks.

There are several reasons why the relation between economic activity and financial markets is stronger at year-end. Barsky & Miron (1989), Beaulieu & Miron (1992), and Beaulieu, MacKie-Mason & Miron (1992) document that movements in economic time series such as GDP, consumption, industrial production, etc. are dominated by what they call the "Christmas demand shock". Likewise, Wen (2002) finds that large fluctuations in macroeconomic variables around Christmas generate larger future business cycles fluctuations. Jagannathan & Wang (2007), page 1625, write that "Investors are more likely to make consumption and portfolio choice decisions at the end of each calendar year because of Christmas and the resolution of uncertainty about end-of-year bonuses and the tax consequences of capital gains and losses". This suggestion is supported by the evidence that investors rebalance their portfolios more significantly at the end of the year; see for instance Ritter & Chopra (1989) and He, Ng & Wang (2004).[2] Therefore, if economic fluctuations at the end of the year are more important for business cycle fluctuations (Wen, 2002) and investors take current economic performance

[2]It is important that we already early on stress that our findings do not reflect a traditional January effect: We also find strong predictability if we predict returns starting from the second quarter, i.e., excluding the first quarter and thus January.

into account when rebalancing their portfolios, which they seem to do to a significant extent at the end of the year (Ritter & Chopra, 1989), expected returns will be relatively more affected by end-of-the-year economic activity, as we find.

Related literature. Our paper is inspired by Jagannathan & Wang (2007; JW) and thus also related to Jagannathan *et al.* (2012; JMTW), Møller (2008), and Da & Yun (2010; DY).

JW, JMTW, and DY study static consumption-CAPMs. Our focus is different: We study time-variation in expected returns. In addition, we study the relation between fourth-quarter economic growth and economic confidence in order to explain why end-of-the-year economic growth is so special.

In more detail, JW, JMTW, and DY show that the annual fourth-quarter to fourth-quarter change in consumption or electricity consumption (DY) captures the cross-sectional variation in average returns. Our novel result is that third-to-fourth quarter growth in basically any macroeconomic variable, i.e., not only consumption, captures time-variation in expected returns. We show that fourth-quarter economic growth rates contain strong out-of-sample information, even using vintage data available to the investor in real time. Importantly, we also show that fourth-quarter economic growth predicts the world-market portfolio as well as different regional non-U.S. portfolios, i.e., this is not only a U.S. phenomenon.[3] Finally, and perhaps even most importantly, we examine economic reasons why fourth-quarter economic growth rates contain so much information about future returns by showing that confidence (consumer and business) growth and economic growth are related during the fourth quarter, but not during the other quarters. This provides an explanation why fourth-quarter economic growth is strongly related to expected returns.

Our paper is, of course, also related to the large general return-predictability literature (for surveys, see Campbell, 2003; Cochrane, 2007; Lettau & Ludvigson, 2010; and Rapach & Zhou, 2011), and, within this literature, more specifically to those papers that deal with the relation between time-series movements in expected returns and macroeconomic variables such

[3] JMTW study Japan and the U.K. using static CCAPMs. We study time-variation in expected returns on the world-market portfolio and broad regional portfolios.

as Cochrane (1991), Lamont (2000), Lettau & Ludvigson (2001), Lustig & van Nieuwerburgh (2005), Santos & Veronesi (2006), Rangvid (2006), Cooper & Priestley (2009), and Belo & Yu (2012). Our contribution to this literature is to show that one finds strong return predictability by pure non-estimated macroeconomic variables if focusing on the fourth-quarter growth rate, but not otherwise, thereby showing that there actually is a strong link between movements in business cycle variables and future returns; something the literature has called upon (see footnote 1). In addition, we focus not only on the U.S. equity market as is often done in the literature, but provide results also for bonds and foreign equity markets as well as out-of-sample predictability evidence. We are also related to those papers that investigate the relation between consumer confidence and expected returns such as Charoenrook (2003), Fisher & Statman (2003), Ludvigson (2004), Brown & Cliff (2005), Qui & Welch (2006), Lemmon & Portniaguina (2006), and Schmeling (2009). In relation to this literature, we show that the fourth-quarter change in consumer confidence (and business confidence) is a stronger predictor of returns than consumer confidence (and business confidence) during the other quarters. This is a new finding in the consumer confidence-expected returns literature.

Finally, even if our paper is empirical in nature, it is related to the literature that models time-varying expected returns via time-varying preferences, such as Campbell & Cochrane (1999) and Bekaert *et al.* (2010), as we find expected returns to be high during bad economic times. Given that we find this to be the case during the fourth quarter of the year, our paper is related to those papers that analyze models with seasonal patterns in preferences, such as Miron (1986), Ferson & Harvey (1992), Braun & Evans (1995), and, more recently, Kamstra *et al.* (2011) and Jagannathan *et al.* (2012). We are also related to the literature on infrequent portfolio decisions, such as Duffie & Sun (1990), Lynch (1996), Abel *et al.* (2007, 2011), and Bacchetta & van Wincoop (2010), as we demonstrate an infrequent feature characterizing the relation between economic growth and expected returns.

The rest of the paper proceeds as follows. In the next section, we describe the data we use. In Section 3, we provide comprehensive evidence that the fourth-quarter growth rates of many macroeconomic variables capture movements in expected returns in the U.S. and abroad, from stock and bonds, and in-sample and out-of-sample. In Section 4, we turn to the question of why the fourth-quarter growth rate is such a strong predictor by showing that economic growth is correlated with growth in economic confidence during the fourth quarter of a year. In Section 5 we analyze economic mispricing and risk-compensation reasons for this relation. A final section concludes.

2 Data

2.1 U.S. data

The business cycle variables we focus on are the quarterly growth rates of seasonally adjusted industrial production, real GDP, and real per capita consumption of services and non-durable goods. Later, in Section 4.3, we show that we find similar results to those reported below using many other business cycle variables. By using both national account data (GDP and consumption) and explicit production (industrial production) data, we make sure that our results are not driven by a particular choice here.

Real GDP is directly downloadable and no data transformations have been done (except converting to quarterly growth rates, of course).[4] As consumption, we use real per capita consumption of non-durables and services in order to be consistent with Jagannathan & Wang (2007). To save space, we refer to this paper for details on data construction and sources. Industrial production is available at a monthly frequency.[5] We use the quarterly averages as our quarterly series to compare with the other macro series, but also show results using the monthly observations.

Quarterly national accounts are available from 1947. In our regressions, we use 1948 as the first observation because we compare the fourth-quarter growth rate with the growth rates of the other quarters, and the first first-quarter growth rate (the change from the fourth to the first quarter) of the national accounts data (GDP and consumption) is the one from 1948, i.e.,

[4] Data are from St. Louis Fed's FRED database: http://research.stlouisfed.org/fred2/series/GDPC96?cid=106

[5] Data are from St. Louis Fed's FRED database: http://research.stlouisfed.org/fred2/series/INDPRO?cid=3

the growth from 1947:4 to 1948:1. Starting in 1947 for the second, third, and fourth quarter would not change the results to any noteworthy extent. Our last observation is 2009:4.

For our main results, we use the CRSP value-weighted index including NYSE, AMEX, and NASDAQ stocks to calculate the returns on stocks. In addition, we show results from predictions of excess returns on firms in the CRSP equal-weighted index. We calculate quarterly stock returns from which we subtract the short-term Treasury Bill rate in order to calculate excess returns on stocks. We also work with annual excess returns which are calculated by rolling over quarterly returns over the coming four quarters, i.e., $R^e_{t+1} = (1+R^m_{t\to t+1Q})(1+R^m_{t+1Q\to t+2Q})(1+R^m_{t+2Q\to t+3Q})(1+R^m_{t+3Q\to t+4Q})-(1+R^f_{t\to t+1Q})(1+R^f_{t+1Q\to t+2Q})(1+R^f_{t+2Q\to t+3Q})(1+R^f_{t+3Q\to t+4Q})$, where R^m is the market return on stocks and R^f is the risk-free rate.

We compare the predictive performance of the fourth-quarter consumption growth series with the predictive performance of a set of commonly used predictive variables. We use three standard predictive variables: The dividend-price ratio, DP (see, e.g., Campbell & Shiller, 1988, and Fama & French, 1988, 1989), the spread between long-term government bond yields and Treasury bill yields, TMS (see, e.g., Campbell, 1987, and Fama & French, 1989), and the $\widehat{cay}$-ratio of Lettau & Ludvigson (2001). DP is calculated as the ratio between the CRSP dividends and the CRSP value-weighted stock index using 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. The cointegration residual $\widehat{cay}$ is the estimated consumption-wealth ratio proposed by Lettau & Ludvigson (2001), and we obtained it from Amit Goyal's website. All benchmark predictive variables are measured on an annual frequency.

2.1.1 Summary statistics

In Table 1, we provide summary statistics for the predictors we use. The table reports the average quarterly growth rates, standard deviations, and the first-order autoregressive coefficients, and, in the lower part of the table, the correlations between the time series of the fourth-quarter growth rates. G^1 is the first-quarter growth rate, i.e., the growth rate between the fourth and first quarter of a year, G^2 the second-quarter growth rate, G^3 the third-quarter growth rate, and G^4 is the fourth-quarter growth rate, i.e., the growth rate between the third and the fourth quarter of a year.

The data are seasonally adjusted so there are no particularly notable differences between the summary statistics of the different quarters. But some notable features of the data are that the growth rates of the per capita consumption series are lower than the GDP growth rates due to population growth. We also note that the industrial production series is more volatile than the other business cycle variables. This higher volatility of industrial production is also visible from Figure 1, where we provide the time-series behavior of the fourth-quarter growth rates together with indications if there is a NBER-defined recession during the fourth quarter of a particular year. Of course, as is also clear from the figure, the Q4-variables reach their lowest value during recessions, i.e., are low during severe economic downturns.

3 Fourth-quarter economic growth and expected returns

3.1 In-sample U.S. equity return predictions

In this section, we first show in Table 2 the results from regressing U.S. one-year ahead excess stock returns on the quarterly growth rates of the different macroeconomic variables in-sample, i.e., results from the regression:

$$R^e_{t+1} = \alpha + \beta G^i_t + \varepsilon_{t+1}, \tag{1}$$

where R^e_{t+1} is the one-year-ahead excess return on stocks, and G^i is the quarter i growth rate of one of the business cycle variables. For G^4, the change from the third to the fourth quarter of a year, the one-year-ahead excess stock return is measured over the calendar year. 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, and so on for G^2 and G^3. At the bottom of the table, we show results from using the benchmark variables as predictors, predicting calendar year returns. For each regression, we report the slope estimate, the Newey-West corrected t-value (truncated at lag 2; our results are very robust towards other choices of truncation lags), and the adjusted R^2-statistic.

We first describe results from predictions of returns on the value-weighted portfolio. The initial point to notice is that all fourth-quarter economic growth rates are strongly significant; the t-statistic is at least -4.88 (using consumption) and gets as high as -5.74 (using industrial production). These are very high t-statistics in this kind of regression. For instance, $\widehat{cay}$ generates a t-statistic of 3.65 and the dividend yield a t-statistic of 3.07. Likewise, the $\bar{R}^2$s from using the fourth-quarter growth rates are high too: The $\bar{R}^2$s are all above 15%. Among the benchmark variables, $\widehat{cay}$ generates the highest $\bar{R}^2$ of around 12% – clearly lower than those generated by most of the fourth-quarter growth rates. Finally, we notice that the estimated signs to the coefficients are negative, as expected, such that a negative (positive) movement in economic growth during the fourth-quarter raises (lowers) expected returns. We return to the more detailed interpretation of this sign in Section 4.

DP and $\widehat{cay}$ are persistent variables; the AR(1) coefficient of DP is 0.90 and that of $\widehat{cay}$ 0.72. From Stambaugh (1999), it is well-known that such persistence influences inference in predictive regressions. Building on the work of Stambaugh (1999), Amihud & Hurvich (2004) and Amihud *et al.* (2009) provide a simple augmented regression method to bias adjust the predictive coefficient and test hypotheses. Using their procedure, we find that DP becomes insignificant (bias adjusted t-statistic equal to 1.94), whereas $\widehat{cay}$ remains significant with a slightly smaller t-statistic (bias adjusted t-statistic equal to 2.92). Given the low persistence of G^4 (as shown in the "AR1" rows in Table 1), on the other hand, it is not surprising that the effect of the bias correction on the significance of G^4 is virtually non-existing.

We create two simple predictors where we use the information available in all the different fourth-quarter growth rates: A simple average of the fourth-quarter growth rates of real GDP, real consumption, and industrial production, and the first principal component of these series. When used in the predictive regression, the simple average of the three Q4-variables generates an $\bar{R}^2$ of 20.37% with a t-statistic of -6.76. To our knowledge, the large return predictability literature has not previously produced such a simple (i.e., not based on estimated coefficients) predictor with such a high t-statistic in a predictive regression using non-overlapping annual excess returns. The principal component generates a t-statistic of -7.65 and an $\bar{R}^2$ of 21.78%; also impressive, but here we are of course using forward-looking information when forming this variable because the coefficients used to generate the principal component are based on the full sample of information.

Our results are robust to the timing of the returns we forecast. This is comforting because macroeconomic data are released with a lag. For instance, the final estimates for the previous fourth-quarter national account figures are typically released near the end of March. Hence, we also regressed one-year-ahead excess returns from the beginning of the second quarter to the end of the first quarter next year on the Q4-variables. The results are much in line with those reported in Table 2. Instead of showing these in-sample results here, we show in Section 3.2 results from out-of-sample tests where we use returns moved forward one quarter, i.e., returns arising after the release of the final estimates of macroeconomic variables in March. We did another check of the importance of the timing of returns. In Table 2, we predict returns over different one-year periods, each commencing after the end of the quarter we look at, as explained in the text above and in the note to Table 2. To make sure that this choice of timing of the returns we forecast does not influence our conclusions, we also predicted the same one-year ahead return for all quarterly economic growth rates, i.e., using both Q1, Q2, Q3, and Q4 economic growth to predict calendar-year returns, using both Q1, Q2, Q3, and Q4 economic growth to predict Q1-Q1 returns, etc. We find that Q4 economic growth rates predict Q4-Q4 (calendar year) returns, Q1-Q1 returns, marginally Q2-Q2 returns, but not Q3-Q3 returns. None of the other quarterly economic growth rates predict returns at any point in time. Hence, only Q4 economic growth rates contain information about expected returns, regardless of how we time the returns we predict.

Jagannathan & Wang (2007) and Da & Yun (2010) focus on annual fourth-quarter to fourth-quarter (Da & Yun: December-to-December) changes in consumption or electricity consumption and its relation to the cross-sectional variation in mean returns. We focus on several additional macroeconomic time series, i.e., not only consumption, but we also focus on the quarterly change in these series from the third to the fourth quarter, and their relation to time variation in expected returns. We focus on the quarterly Q3-Q4 growth rate, and not the annual Q4-Q4 growth rate, because the major part of information about expected returns is contained in the third-to-fourth quarter change. We can show this using consumption first. Regressing next year's excess return on the annual change in consumption from last year's fourth quarter to this year's fourth quarter (the consumption growth rate that Jagannathan & Wang use), we find a t-statistic of -3.25 and an $\bar{R}^2$ of 9.50%. This can be compared with the information contained by G^4 as shown in Table 2: t-statistic of -4.88 and an $\bar{R}^2$ of 16.05%. Hence, the Q4-Q4 consumption growth rate also predicts returns, but to a considerably lower degree than the change in consumption from Q3 to Q4. To understand this better, we can split the change from last year's Q4 level of consumption to this year's Q4 level of consumption into the first three quarters ($(1+G^1)\times(1+G^2)\times(1+G^3)-1$) and the fourth-quarter (G^4). The t-statistic from using the Q4-Q3 ($=(1+G^1)\times(1+G^2)\times(1+G^3)-1$) consumption growth rate, i.e. consumption growth during the first three quarters, is only -1.85 and the $\bar{R}^2$ is 2.95%. Hence, it is the fourth-quarter growth rate that gives rise to the predictability found using annual Q4-Q4 growth – the first three quarters basically do not predict returns.

The same is true for the other macroeconomic growth rates. Using the annual Q4-Q4 change in GDP, we find a t-statistic of -1.88 and an $\bar{R}^2$ of 4.54%. This can be compared to the t-stat (seen from Table 2) of -4.95 and $\bar{R}^2$ of 15.40% we find when using the quarterly Q3-Q4 growth rate. For industrial production, we find a t-statistic of -1.71 and an $\bar{R}^2$of 4.23% when using annual Q4-Q4 growth rates. Again, these are considerably lower than the statistics we show in Table 2. So, the quarterly Q3-Q4 growth rates contain a very large amount of information about expected returns, whereas the Q4-Q3 ($=(1+G^1)\times(1+G^2)\times(1+G^3)-1$) change contains almost nothing.

We can relate these findings to the common perception in the literature (as expressed, for instance, by the quote from Lettau & Ludvigson (2010) in footnote 1) that economic growth does not predict returns. If we run a standard predictive regression of next quarter's excess return on this quarter's growth rate in industrial production using all quarters, we find the slope coefficient to be insignificant and the R^2 is close to zero percent. In other words, one only sees the predictive power of economic growth when focusing on the fourth-quarter growth rate, and not from a typical time-series regression that uses all observations.[6]

A recent literature focusing on traditional predictor variables argues that excess return predictability is concentrated to a few periods surrounding recessions; see, e.g., Henkel, Martin & Nardari (2011) and Rapach, Strauss & Zhou (2010). We checked whether Q4 predictability is concentrated to recessions by interacting our Q4-variables with a recession dummy in the regression $R^e_{t+1} = \alpha + \beta I_t G^4_t + \varepsilon_{t+1}$ where I_t equals one if there is a NBER-defined recession in the fourth quarter of the year, and we interact the predictors with $(1 - I_t)$ in an expansion regression $R^e_{t+1} = \alpha + \beta(1 - I_t)G^4_t + \varepsilon_{t+1}$. We find that the simple average of the three Q4-variables is a significant predictor during both expansions and recessions with a t-statistic of -3.59 and an $\bar{R}^2$ of 9.86% in expansions, and a t-statistic of -8.44 and an $\bar{R}^2$ of 21.68% in recessions, i.e., predictability by Q4 variables is not confined to recessions, even if stronger during recessions.

Finally, in the last column in Table 2, we show results from predictions of the return on the equal-weighted CRSP portfolio. We just show the results we get when using the fourth-quarter growth rates to predict; like for the value-weighted portfolio, the first-, second-, and third-quarter economic growth rates are not significant predictors of future returns on the equal-weighted portfolio. The main take-away is that fourth-quarter economic growth rates predict returns on both small-cap and large-cap firms, as the results for the equally-weighted portfolio are similar to the results for the value-weighted portfolio; if anything, the results are slightly stronger for the equal-weighted portfolio. We show below that when we concentrate on subsamples of the full sample, though, differences between the predictability of returns on the equal-weighted and the value-weighted portfolios appear.

[6] The same conclusion holds if we predict next year's return instead of next-quarter's return using all observations and not only the fourth-quarter observations. In spite of overlapping observations in such a regression, this regression also yields insignificant relations.

Long-horizon cumulative returns. The predictive power of Q4-variables builds up over the next year, and then declines for cumulative returns over more than one year. We see this from Table 3 that shows results from standard long-horizon regressions $R^e_{t,t+h} = \alpha + \beta X_t + \varepsilon_{t,t+h}$, where $R^e_{t,t+h}$ is the excess return obtained over h quarters. To save space, we show in Table 3 only the results obtained when using industrial production to predict. The results we find using the other business cycle variables are similar to the results shown in Table 3. We find that Q4-variables are strong predictors of medium-term (up to one year) returns, but not longer-term returns: When predicting two-year cumulative returns, the R^2 drops from its 17.93% at the one-year horizon to only 8.55%, and three-year cumulative returns are not even predictable to a significant extent. This is different from results in the literature using persistent predictors such as the dividend yield. The R^2s and t-statistics from regressions using persistent predictors mechanically increase with the horizon and several papers discuss the potential biases that arise in long-horizon predictive regressions when the predictor is persistent (see, e.g., Valkanov, 2003 and Boudoukh *et al.*, 2008). Q4-variables are not persistent predictors as shown in Table 1 and seen from Figure 1. For this reason, the fact that the $\bar{R}^2$ rises with the horizon up to $h = 4$ simply reflects that Q4-variables capture the returns of different quarters of a year, and not just one quarter of the year. We also see from the table that none of the other quarters' growth rates predict returns at any horizon. Finally, in the lower part of Table 3, we show results from predictions of long-horizon returns on the equal-weighted portfolio. Like in Table 2, there are no particular differences to the results from the value-weighted portfolio.

Monthly observations. We focus on quarterly observations in our paper as most macrovariables are available at a quarterly frequency only. Within the fourth quarter, however, December is probably "special" due to Christmas, New Year, and end-of-year features such as tax filings, bonuses, etc.[7]

Industrial production is available at a monthly frequency going back far in time. In order

[7] We mentioned in the Introduction to this paper that Barsky & Miron (1989) refer to the special business cycle feature of the fourth quarter as a "Christmas demand shock", Wen (2002) calls the effect he identifies the "business cycle effects of Christmas", and Jagannathan & Wang (2007) also point to the turn of the year as something special.

to evaluate the monthly evidence, we show in Table 4 results from regressions using monthly growth rates of industrial production to predict one-year ahead excess returns. There are two clear findings: First, the months in the fourth quarter are all special as October, November, and December growth rates all predict both the value- and the equal-weighted portfolio, whereas the other months do not predict returns (September predicts the equal-weighted portfolio but not the value-weighted, though). Second, December contains more predictive power than November and October (and any other month) as coefficient estimates, (numerical) t-statistics, and R^2s are all higher using December growth rates to predict. This suggests that a large part of the quarterly action we document in this paper is due to the December growth rate as one would intuitively expect given December's special role in the calendar year. November and October also contain information, possibly due to days such as Thanksgiving and Black Friday Shopping in November and economic activities preceding these end-of-the-year events.

3.2 Out-of-sample predictability

Goyal & Welch (2008) show that returns might be predictable in-sample, but difficult to predict out-of-sample. Goyal & Welch (2008) also show that the main reason for the poor out-of-sample performance of many predictor variables is that predictive regressions are plagued by estimation instability.

There are two features that can cause out-of-sample forecasts using macroeconomic variables to differ from in-sample forecasts. First, in out-of-sample forecasts, the coefficients in the predictive model might change over time compared to the assumption of constant predictive coefficients in in-sample forecasts. Second, the time series available today might be different from the ones available in real time due to data revisions. Where parameter instability is the usual concern in out-of-sample tests (Goyal & Welch, 2008), the issue of data revisions is special to macroeconomic variables. The issue of data revisions is also treated differently in different studies. For instance, in the seminal paper of Lettau & Ludvigson (2001), they use the today-available (and thus revised) consumption series in their out-of-sample tests, whereas Cooper & Priestley (2009) use two measures of the output gap in their analysis: One (the one that they primarily focus on in their analysis) based on real-time vintage industrial output, and one based on today-available and hence revised GDP.

To be on the safe side, we present results using both kinds of macroeconomic series. As our first step, we follow Lettau & Ludvigson (2001) and use the today-available revised series. Of course, this analysis is not representative for how a real-time investor could have performed because of data revisions. The analysis will, though, illustrate how sensitive the forecast performance is towards allowing for time-varying forecast parameters. To investigate how a real-time investor could have performed, we show in a second step that our results are robust to using real-time vintage data.

Our out-of-sample forecasting procedure is as follows: First, we estimate the unrestricted forecasting model $R^e_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$ using data from 1948 to 1974 and make a forecast for 1975. Then, we re-estimate the model using data from 1948 to 1975 and make a forecast for 1976. This procedure continues until the end of the sample in 2009, i.e., our out-of-sample period is 1975-2009. In a similar way, we generate out-of-sample forecasts using a restricted forecasting model with $\beta = 0$: $R^e_{t+1} = \alpha + \varepsilon_{t+1}$. Let $\hat{\varepsilon}_{U,t+1} = R^e_{t+1} - \left(\hat{\alpha}_{U,t} + \hat{\beta}_{U,t} X_t\right)$ denote the forecast error using the unrestricted forecasting model, and let $\hat{\varepsilon}_{R,t+1} = R^e_{t+1} - \hat{\alpha}_{R,t}$ denote the forecast error using the restricted forecasting model with $\beta = 0$. The out-of-sample statistics that we calculate are then given by:

$$R^2 = 1 - \frac{MSE_U}{MSE_R}, \tag{2}$$

$$ENC\text{-}NEW = \frac{\sum_{t=1}^{T}\left(\hat{\varepsilon}^2_{R,t+1} - \hat{\varepsilon}_{R,t+1} \times \hat{\varepsilon}_{U,t+1}\right)}{MSE_U}, \tag{3}$$

$$MSE\text{-}F = T \times \frac{MSE_R - MSE_U}{MSE_U}, \tag{4}$$

where MSE_U is the mean squared error of the unrestricted model, MSE_R is the mean squared error of the restricted model, and T is the number of out-of-sample forecasts.

The OOS R^2 in Eq. (2) measures the percentage reduction (or increase) in the mean squared forecast error of the model compared to the mean squared forecast error of the historical mean model. A positive OOS R^2 therefore implies that the unrestricted forecasting model generates smaller forecast errors than the restricted forecasting model (the historical mean model). We rely on three forecast comparison tests. Clark & McCracken's (2001) ENC-NEW statistic, defined in Eq. (3), tests the null hypothesis that the restricted forecasting model encompasses the unrestricted forecasting model. McCracken's (2007) MSE-F statistic, defined in Eq. (4), tests the null hypothesis that the restricted forecasting model has a mean squared error that is less than, or equal to, that of the unrestricted forecasting model. Both the ENC-NEW and MSE-F statistics have non-standard distributions, and we use the asymptotically valid critical values provided by Clark & McCracken (2001). Finally, we checked our results using the adjusted procedure recommended in Clark & West (2007). This procedure calculates an adjusted relative (to the benchmark model) squared forecast error and regresses it on a constant to test for significance. Clark & West (2007) show that this statistic has the additional advantage that standard normal asymptotic critical values are close to actual sizes, and they provide simulation evidence showing that this holds true in small samples. We use Newey-West standard errors and label the test $t(NW)$ in the tables. The results are qualitatively identical if using OLS standard errors instead of NW standard errors.

3.2.1 Today-available data

Given that final estimates for the national account data are released during March,[8] we predict returns from the beginning of the second quarter of the year to the end of the first quarter next year in order to better reflect the situation of a real-time investor.[9] In Table 5, upper panel, we show results from out-of-sample predictions using the today-available and thus revised data. Table 5 shows that Q4-variables are strong predictors of excess returns also out-of-sample. The out-of-sample R^2s are generally around 10% (9.75% using consumption and up to 12.57% using GDP), and the ENC-NEW, the MSE-F, and the $t(NW)$ test statistics all indicate statistically significant out-of-sample predictability. These results are in stark contrast to the

[8] Advance, preliminary, and final estimates for the previous fourth quarter are typically released near the end of January, February, and March, respectively.

[9] We have also used calendar-year returns in this setting. The results do not change significantly compared to those in Table 5.

Goyal & Welch (2008) results that we illustrate in the lower part of Table 5, where we use DP, TMS, and $\widehat{cay}$. In spite of their extended use as predictors in the literature, DP and TMS do not generate significant out-of-sample predictability, and in fact predict worse than the historical mean as seen via the negative OOS R^2s. $\widehat{cay}$ also generates a positive OOS R^2, but $\widehat{cay}$ is an estimated regressor, i.e., there is some degree of look-ahead bias involved in the construction of $\widehat{cay}$ (Guo, 2009 discusses this). In addition, the OOS R^2s that the Q4-variables generate are considerably higher than the OOS R^2 that $\widehat{cay}$ generates.

Table 5 shows results using fourth-quarter growth rates. Using other quarters' growth rates generates results like the in-sample results in Table 2: It is only the fourth-quarter growth rate that predicts returns out-of-sample; economic growth during the other quarters does not.

The last column in Table 5 shows the results we get when we predict returns on the equal-weighted portfolio out-of-sample. It is apparent that small-cap stocks are even more predictable (R^2s are even higher) out-of-sample; we find OOS R^2s around 20% – these are very high out-of-sample R^2s in light of the Goyal & Welch findings, summarized here via the results we get using DP, TMS, and $\widehat{cay}$. Given that the out-of-sample predictions are done over the period from 1975 and onwards, this indicates that there are differences in the extent to which we can predict returns on large-cap stocks and small-cap stocks during the last couple of decades. In Section 3.3, we investigate this in more detail.

3.2.2 Vintage data

A real-time practitioner who uses economic growth during the fourth quarter to improve his forecast of excess stock return faces the potentially important concern that annual revisions take place each summer, and comprehensive revisions take place at irregular intervals. In order to examine the extent to which our out-of-sample results are sensitive to announcement delays and data revisions, we construct a real-time data set 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 2009, 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. We assume that the real-time practitioner uses the final estimates from each vintage – available near the end of March – to make forecasts of R^e_{t+1}, with R^e_{t+1} again being the return obtained from April 1 to March 31 the year after.

We show the results from out-of-sample tests using vintage data in Table 5.[10] The point to stress from this table is that economic growth during the fourth quarter is also in real time a convincing and significant predictor of excess returns out-of-sample: The out-of-sample R^2s are between approximately nine and twelve percent for the value-weighted portfolio (and between ten and twenty percent for the equal-weighted portfolio), and the null hypotheses of equal forecasting power of the restricted and unrestricted models are strongly rejected. The out-of-sample R^2s are also considerably higher than the OOS R^2 of the benchmark variables. In other words, even if using real-time data, the fourth-quarter consumption growth rate predicts returns better than any of the other commonly used predictors do out-of-sample and also significantly better than the historical mean that Goyal & Welch (2008) report is difficult to "beat".

3.2.3 Quality of data

With the vintage data, we can also investigate whether early releases of fourth-quarter data are "superior" in terms of their precision/quality. If this was the case, it would be rational for investors to put relatively more emphasis on fourth-quarter economic data when judging the outlook for financial markets. Hence, we calculated the average "errors" in the data by comparing the average revisions of fourth-quarter economic data (comparing first-release data with the revised data available now) with the average revisions of first, second, and third quarter economic data. Basically, the average revisions are more or less of the same sizes across the different quarters. Hence, it is not simply the quality of the data that makes the fourth quarter special.

[10] Real-time vintage GDP data are not available for the 1975-1992 period. For this reason, the table reports results using vintage data for industrial production and consumption.

3.3 Subsample analysis

The out-of-sample results have revealed that returns on both the value-weighted and the equal-weighted portfolios are predictable in real time. The results have also revealed, though, that there seems to be differences in the degrees of predictability of returns on small-cap and large-cap firms during the last couple of decades. To investigate this in further detail, we show in Table 6 results from subsample regressions. We split the full sample in two and show results for the 1948-1979 and the 1980-2009 periods. To verify that our results are not driven exclusively by the 2008-2009 crisis, we also look at the 1980-2007 period. We show results for predictions of the value-weighted (VW) and the equal-weighted (EW) portfolios, respectively, using fourth-quarter growth rates of the different macroeconomic variables, the benchmark variables, and the average (AVE) of the fourth-quarter growth rates of the macroeconomic variables.

The first thing to notice is the insight from Goyal & Welsh (2008) and Ang & Bekaert (2007) that returns have been more difficult to predict after the oil crisis of the mid-1970s using standard predictive variable: DP and $\widehat{cay}$ display very strong predictive power during the 1948-1979 period, whereas there is almost no predictive power after 1980. This holds for both value-weighted and equal-weighted returns. For the fourth-quarter economic growth rates, the situation is different: Fourth-quarter economic growth rates strongly predict the return on the equal-weighted portfolios also after 1980 with R^2s above ten percent and up to around twenty percent. For instance, the average of C, GDP, and IP yields an R^2 of 23.16% for the 1980-2009 period. For the value-weighted portfolio, however, the results are somewhat like those for the benchmark variables; the R^2s are considerably lower than those for the 1948-1979 period, and consumption and GDP are significant, whereas industrial production is not. Finally, the 1980-2007 results are significant, too. All in all, we conclude that even when it has become more difficult to predict excess returns after the mid-1970s using standard predictor variables, as Goyal & Welsh (2008) and Ang & Bekaert (2007) report, excess returns are nevertheless predictable by fourth-quarter economic growth rates. In particular, returns on the equal-weighted portfolio have been strongly predictable during these recent decades by fourth-quarter economic growth rates.

3.4 International evidence

Fourth-quarter, and only fourth-quarter, growth rates predict returns not only in the U.S. but also world-wide. To show this, we regress one-year ahead excess returns in U.S. dollars (stock returns in USD minus the U.S. risk-free rate) from the MSCI World, MSCI World excl. US, MSCI EAFE (Europe, Australia, and the Far East), and MSCI Europe on quarterly growth rates of industrial production. We use two measures of industrial production to predict these global returns: Quarterly growth rates of G7 industrial production and an equal-weighted series of quarterly growth rates of industrial production in Australia, Belgium, France, Germany, Japan, Italy, Netherlands, Sweden, Switzerland, the U.K. and the U.S.[11] The sample period is 1970-2009.

The results are in Table 7: We find a clear and strong global Q4 effect. Looking at the results for the world-market portfolio first, we see that – exactly like in Table 2 for U.S. results – first-quarter, second-quarter and third-quarter growth rates are insignificant predictors of future returns and generate negative $\bar{R}^2$s, whereas fourth-quarter growth rates are highly significant predictors with t-statistics above three and $\bar{R}^2$s being either 6.63% (using the G7 series) or 8.61% (using equal-weighted growth rates from even more countries). We stress that these results are for the 1970-2009 period, i.e., the period where returns on U.S. large-cap stocks are more difficult to predict as shown in Table 6 and Goyal & Welsh (2008). Finally, we notice that the sign to the fourth-quarter growth rate is consistently estimated: In all regressions, a negative movement in the Q4 growth rate of industrial production increases next year's expected return.

Looking at returns from a global portfolio without U.S. returns (results for "World ex US"), we find similar kinds of results, i.e., fourth-quarter growth rates predict, whereas growth rates of other quarters do not. The same is found when looking at returns from Europe, Australia, and the Far East, and when looking at Europe on its own. Our conclusion is that it is not only U.S. Q4 variables that predict U.S. returns; indeed, the same finding goes through around the

[11] For robustness, we also used the principal component of the national industrial production series, and we calculated a series using the same countries but excluding the U.S. for which we already know it works, as shown in the previous tables, in order to see whether the U.S. drives the results. The results were not qualitatively affected. Likewise, instead of capital market weighted returns, we used GDP weighted returns. Again, results were qualitatively unaffected.

world.

3.5 Expected excess returns on bonds

Fama & French (1989) were the first to suggest examining movements in expected returns on both stocks and bonds in order to see whether different risky asset classes behave similarly to a movement in a forecasting variable. Hence, in Table 8, we show results from regressions of excess returns on a two-year zero-coupon bond on the predictor variables. We use the Fama-Bliss data to calculate the returns on bonds. Following Cochrane & Piazzesi (2005), among others, we subtract the 1-year yield when calculating excess bond returns.[12] We find that the fourth-quarter growth rates contain significant information about movements in expected returns on bonds, and that none of the other quarters' growth rates contain such systematic information. The R^2s range from 4.05% using consumption to 9.25% using industrial production. These are lower than when predicting excess stock returns, but still clearly significant. We also checked predictions of excess returns on bonds of different maturities: $n = 2$ years, 3 years, 4 years, and 5 years. We found that the Q4 economic growth rate is a significant predictor of bonds of different maturities, and that the growth rates of macroeconomic variables during other quarters of the year do not predict bond returns of different maturities.

Like for stocks in Table 2, the coefficient estimates to the Q4-variables in the bond-predicting regressions are negative, i.e., a negative shock to a Q4-variable increases expected returns on bonds and stocks. In Section 4, we show that movements in Q4-variables contain information about economic confidence which should affect investors' attitude to investing in risky assets – bonds and stocks – in the same direction. It is comforting that this is what we find.

4 Economic growth and confidence

We now turn to explanations for the strong predictability patterns that we have discussed in the preceding section. We suggest that fourth-quarter economic growth induces a cyclical

[12] As robustness, we also calculated an excess return on bonds where we subtract the 1-month T-bill rate. The qualitative nature of the results remains unchanged.

component in economic confidence that in turn influences expected returns. Our starting point is the general observation that expected returns will be time-varying if the price of consumption risk is time-varying, and that the price of consumption risk depends on the level of risk aversion in the economy (see, e.g., Campbell & Cochrane, 1999): In time periods where aversion towards risk is high, expected returns will be high too. This means that if regressing excess returns on a variable that correlates negatively with aggregate risk aversion in the economy, the slope coefficient in the return-predicting regression will be negative as we find in our regressions. In other words, when economic growth during the fourth quarter is high, risk aversion and expected returns are low.[13]

It has been suggested that consumer confidence is related to risk aversion (Qiu & Welch, 2006; Lemmon & Portniaguina, 2006), possibly via the relation between financial wealth and risk aversion (Brav et al., 2002; Malloy et al., 2009; and Wachter & Yogo, 2010).[14] Hence, we investigate in this section the relation between economic growth and consumer confidence as an empirical proxy for risk aversion. The intuition for how consumer confidence influences risk aversion is straightforward: If consumers feel less confident with respect to their consumption possibilities, they will also be more averse against taking on financial risk as it could imply – if returns turn out to be low – that future consumption will be even lower. When consumers feel confident, on the other hand, their aversion against taking on risk is lower.

We proceed in two steps. We first provide statistical evidence that economic growth and growth in consumer confidence are positively related during the fourth quarter but not during the other quarters. Next, we show that consumer confidence during the fourth quarter is a stronger predictor of returns than consumer confidence during the other quarters.

The University of Michigan and the Conference Board provide reasonably long time-series of consumer sentiments. Ludvigson (2004) in detail discusses the construction of the two measures, their differences, and their relative merits. To be on the safe side, we report results using both series. The University of Michigan data are available for the 1960:1-2009:4 period and the

[13] Our finding that this relation appears during specific points in time means that it is not a pure Campbell-Cochrane (1999) finding we have, but more likely preferences with a seasonal component to them.

[14] One of the questions in the University of Michigan's consumer survey is whether consumers "feel better or worse off financially".

Conference Board data for the 1967:1-2009:4 period. The Conference Board data are seasonally adjusted whereas the University of Michigan data are not. We seasonally adjust the University of Michigan data using the X12 procedure in order for both series to be seasonally adjusted.

We regress the quarterly growth rates of consumer confidence on the quarterly growth rates of industrial production as:

$$\Delta Conf_t^i = \alpha + \beta G_t^i + \varepsilon_t \tag{5}$$

where $\Delta Conf_t^i$ is the change in consumer confidence during quarter i, and G_t^i is the quarter i growth rate in industrial production. Using consumption or GDP gives basically similar results. The results are in the upper part of Table 9. The results reveal that growth in consumer confidence during the fourth quarter is significantly related to economic growth during the fourth quarter, and this holds for all macroeconomic time series. The relationship is positive such that a low (high) economic growth rate during the fourth quarter is associated with a low (high) growth rate in consumer confidence. The relationship during the other quarters is either non-existing or much weaker. In particular, there is no significant correlation between the second- and third-quarter economic growth and growth in consumer confidence. For the first quarter, there is a significant correlation, but the R^2s and (numerical) t-statistics are considerably lower than what they are for the fourth quarter. In Table 11, we show similar results using many other economic variables. We generally find a significant relation during the fourth quarter only.

The special behavior of consumer confidence during the fourth quarter helps us understand why fourth-quarter economic growth rates predict returns with negative signs: A low economic growth rate during the fourth quarter is associated with consumers having lower confidence during the fourth quarter which makes them require higher returns. During the other quarters, there is no such relation, or, if there is, it is much weaker. In the time-series dimension this means that fourth quarters with low growth will be associated with high required returns as confidence is low during such periods, i.e., a negative coefficient in the return-predicting regression.

4.1 Business confidence

In the lower part of Table 9, we present results from our investigation whether there is a similar relation between economic growth and business confidence. As our measure of business confidence, we use the purchasing managers index (PMI) available from the Institute for Supply Management (ISM). The PMI reflects purchasing managers' (of private companies) actual (i.e. not intended) production, new orders, employment, etc. such that the index reflects general tendencies in manufacturing activity. Thus, if the index improves, there is expansion within the manufacturing sector, reflecting confidence in the economy. An advantage of the PMI is that it extends back to 1947. The PMI survey consists of a headline index and five subindices (production, new orders, etc.). We present results using the seasonally adjusted headline index and production index.

The results are in the lower part of Table 9. We find that fourth-quarter growth in the PMI is highly correlated with economic growth during the fourth quarter. We also see, like for consumer confidence, a significant, though smaller, correlation in the first quarter, but nothing in the second and the third. In other words, if the economy is doing well in the fourth quarter, and to a smaller extent in the first, manufacturing firms are increasing their economic activity, whereas firms do not change behavior if the economy is doing well (or bad) in the second or the third quarter.

4.2 Confidence and expected returns

We suggest that fourth-quarter economic growth rates predict returns because confidence – as a measure of risk aversion – is responding to economic growth during the fourth quarter while it is not during the other quarters. Several papers have studied whether consumer confidence in itself predicts aggregate market returns.[15] Ludvigson (2004) finds that consumer confidence predicts next year's stock returns but also that "the result is not, however, robust to the inclusion of a proxy for the log consumption-wealth ratio" (Ludvigson, 2004, page 47), i.e., consumer

[15] Lemmon & Portniaguina (2006) find that consumer confidence forecasts the size premium, but not the value or momentum premiums. Lemmon & Portniaguina do not predict the excess return on the market portfolio.

confidence predicts returns but not strongly. Charoenrook (2003), on the other hand, reports strong predictive power of consumer sentiments. Schmeling (2009) finds predictive power of consumer confidence for future returns in many countries. The general finding in these papers is that the regression coefficient is negative such that low (high) confidence today predicts high (low) future returns.

We have just shown in Table 9 that confidence and economic growth is strongly related during the fourth quarter, but not, or only weaker, during the other quarters. In Table 10, we show results from regressions of excess returns on growth in confidence during the different quarters, i.e., from regressions like $R^e_{t+1} = \alpha + \beta \Delta Index^i_t + \varepsilon_{t+1}$, where $Index$ refers to one of the measures of consumer confidence or business confidence, and the superscript i refers to quarter i. We find that growth in consumer confidence and business confidence during the fourth quarter generally influences expected returns whereas growth during the other quarters does not. We also see that fourth-quarter growth in business confidence is an even stronger predictor of returns than growth in consumer confidence; consumer confidence during the fourth quarter is only a marginal predictor of the value-weighted returns, even if a strong predictor of the equal-weighted returns, whereas the PMI is a strong predictor of both the value- and the equal-weighted portfolios. Consumer confidence at the end of the year thus predicts in particular small-cap stocks, whereas business confidence predicts both small- and large-cap stocks. Confidence (consumer and business) during the other quarters does not predict returns. We think that our finding that a large fraction of the predictive power of consumer sentiments reported in earlier studies is concentrated to the fourth quarter gives an interesting new perspective to the existing literature on consumer sentiments and expected returns.

Subsample results. We showed in Table 6 that returns on the value-weighted portfolio are less predictable after 1980 (the equal-weighted portfolio was strongly predictable). In unreported robustness tests, we investigated whether economic growth is related to growth in consumer confidence also during the post-1980 subperiod, and whether consumer confidence predicts returns post-1980. The details of these results are available upon request, but generally we find that the results shown in Tables 9 and 10 extend to the post-1980 subsample.

4.3 Many more variables

Our main point in this paper is that macroeconomic growth during the fourth quarter predicts returns very strongly. Secondly, macroeconomic growth during the fourth quarter predicts returns because economic growth and economic confidence are positively correlated during the fourth quarter. We have shown these results using three macroeconomic variables.

In this section, we show that we find the same results using many more macroeconomic variables. We have checked these findings using the change in the output gap (either estimated from a quadratic trend as in Cooper & Priestley, 2009, or as the difference between GDP and potential GDP as calculated by the Congressional Budget Office), the change in the investment-capital ratio of Cochrane (1991); downloaded from Amit Goyal's webpage, the change in the housing-collateral ratio of Lustig & van Nieuwerburgh (2005), nonfarm employment growth, labor income growth (we use $\triangle y_t$ from Sydney Ludvigson's webpage), changes in the capacity utilization rate (total industry), nonresidential investment growth, changes in the civilian unemployment rate, changes in average weekly hours in manufacturing, changes in overtime hours, etc., etc.

We show in Table 11 results using the quarterly growth rates of some of these variables to predict returns (left-hand columns) and correlations with consumer confidence growth (right-hand columns).

We think that the results in Table 11 are striking. We find that Q4-growth of many business cycle variables are strong predictors of excess returns and highly correlated with consumer confidence growth during the fourth quarter. During the other quarters there are no such effects.[16] We believe these results convey a very strong message about the relation between economic growth, expected returns, and consumer confidence: Q4, and only Q4, economic growth contains lots of information about expected returns and is correlated with peoples' confidence. This finding is robust and extends across a very large range of macroeconomic variables.

[16] We use value-weighted returns and Conference Board confidence in Table 11. Using equal-weighted returns, the results are generally even slightly stronger than the already strong results in Table 11. Using PMI instead of consumer confidence, the results are overall similar to the results shown in Table 11.

5 A "mispricing" perspective to our results

Consumers' confidence might predict returns because it reflects investors' risk aversion as we argue above. There might be an alternative explanation, however, developed in the literature examining the relation between consumer/investor confidence and expected returns: Consumer confidence might also predict returns because it is related to investors' overoptimism/overpessimism (Brown & Cliff, 2005; Qui & Welch, 2006). According to this explanation, prices are pushed up above their fundamental values in times of high optimism, but over time eventually revert to their fundamental value, i.e., periods with high (low) optimism are followed by lower (higher) returns. In our case, the story would be as follows: Fourth quarters with high economic growth are periods in time where consumers are (over)optimistic. During fourth quarters with high economic growth, investors bid up prices above their fundamental value, i.e., assets become temporarily "mispriced", but prices eventually return to their fundamental value. In other words, fourth quarters with high levels of economic activity, and thus high levels of economic confidence (Tables 9 and 11), predict low future returns because assets become temporarily overvalued. During the other quarters there are no such effects as economic growth and growth in consumer confidence are only weakly correlated during other quarters.

The empirical predictions of the two stories – the risk-compensation story based on a relation between risk aversion and economic growth and the mispricing story based on a relation between overoptimism and economic growth – are identical: Periods with high (low) economic growth are periods with high (low) confidence (which can then reflect either risk aversion or overoptimism/-pessimism), and are followed by periods with low (high) returns. In order to come closer to an identification of what drives the relation between sentiments and expected returns, Baker & Wurgler (2006) examine harder-to-arbitrage stocks, such as small-cap stocks, high-growth stocks, and non-dividend paying stocks, as mispricing due to overoptimism should be clearer for those stocks. In this section, we thus briefly investigate predictive patterns in the cross-section of stocks.

Results for small-cap stock indicate mispricing. Our results in Table 6 for the equal- and value-weighted portfolios indicate that returns of small-cap firms are relatively more predictable by fourth-quarter economic growth than returns of large-cap firms during the post-1980 period, even if they are more or less equally predictable in the early period. The R^2s in Table 10 also indicate that small-cap stocks are more predictable by consumer confidence during the fourth quarter compared to large-cap stocks. Given that small-cap stocks are harder to arbitrage and thus more sensitive to mispricing, as Baker & Wurgler (2006) and Lemmon & Portniaguina (2006) argue, our finding that small stocks are more predictable by fourth-quarter economic growth may be seen as support for the mispricing/overoptimism hypothesis.

Results for growth-stocks and non-dividend paying stocks indicate risk compensation. We next investigate other hard-to-arbitrage stocks, such as high-growth and/or non-dividend paying stocks. We download dividend-yield sorted portfolios and book-to-market sorted portfolios from Ken French's homepage. Our hypothesis is that if high economic growth during the fourth quarter predicts returns because high economic growth is associated with overoptimism and consequently temporary mispricing, we should see fourth-quarter economic growth predict stocks in the high-growth portfolio and stocks in the non- or low-dividend paying portfolio (i.e., the hard-to-arbitrage portfolios) better relative to the lower-growth and higher-dividend stocks. The results are in Table 12. In the upper part of the table, we show results from predictive regressions of returns from book-to-market sorted portfolios on lagged fourth quarter economic growth. In portfolio 1, we have the high-growth firms and in portfolio 10 the low-growth (i.e., value) firms. In the last column, we show results for the portfolio being long in the firms in portfolio 10 and short the firms in portfolio 1. In the lower part of the table, we show results for dividend-yield sorted portfolios. In the "No-dividend" column, we show results for firms that do not pay out dividends, in portfolio 1, we have the firms with the lowest dividend yield, and in portfolio 10, the highest dividend yield firms. In the last column, we show results for the 0-10 portfolio being long in non-dividend paying firms and short in the firms with the highest dividend yield.

The overall finding from Table 12 is that Q4 growth in industrial production is a very strong predictor of the whole cross-section of stocks, with high t-statistics and R^2s. In particular, we do not find that coefficients, t-statistics, and R^2s are clearly higher for hard-to-arbitrage stocks. For instance, we see that (numerical) coefficients, (numerical) t-statistics, and R^2s are generally at least as high, if not higher, for stocks in the middle-portfolios (portfolios 4, 5, and 6) compared to the "extreme" portfolios 1 and 10; the opposite of what would be expected according to a mispricing hypothesis. For dividend-sorted stocks, we do a find large effect (large coefficient estimate) for stocks that do not pay out dividend, but we do not find stronger effects for stocks in portfolios 1 or 2 compared to stocks with high dividend yields. All in all, these results make us reluctant to associate our main findings with a mispricing story.[17]

As a check of our results, we also regressed the different portfolios on the investor sentiment measure of Baker & Wurgler. The results are also in Table 12. In this case, we see the patterns identified by Baker & Wurgler: High-growth portfolios are more predictable with the R^2 being close to 13% for the firms that have the lowest book-to-market ratio and declining to around 7% for portfolios with higher book-to-market ratios. Likewise, firms that do not pay out dividends are highly predictable by the investor sentiment index of Baker & Wurgler whereas firms with high dividend yields are not predictable at all.[18]

6 Conclusion

Our story in the paper is as follows. We find that negative (positive) movements in economic growth during the fourth quarter strongly predict high (low) future excess returns. We find this for bonds, all sorts of stock portfolios (aggregate and characteristics-sorted portfolios) in the U.S. in-sample and out-of-sample, and for global portfolios. We also find economic growth to be strongly positively correlated with growth in consumer confidence and business confidence during the fourth quarter. So, bad (good) economic growth at the end of the year goes hand-

[17] We also regressed these portfolios on fourth quarter growth in consumer sentiments and the PMI. Again, we find that we cannot say that mispricing clearly is at work.

[18] We do not think that this is a suitable place to commence a longer investigation why Q4 growth rates give different results compared to the investor sentiments of Baker & Wurgler. We do note here, though, that investor sentiments have a low correlation with economic growth (the correlation is -0.05 with fourth-quarter growth in industrial production). For this reason, it is not surprising that we find different results using fourth-quarter economic growth rates compared to using the investor sentiments of Baker & Wurgler.

in-hand with low (high) confidence in the economy and thereby increases (decreases) the return investors require for holding risky assets when times are bad (good). Because confidence is not, or only weakly, correlated with economic growth during the other quarters of the year, movements in economic growth during the other quarters do not affect expected returns.

Taken together, the findings in the paper suggest a special role of end-of-the-year economic growth for the time-series properties of asset prices, opening up a number of areas in the intersection between finance and macroeconomics that call upon further examination. In Møller & Rangvid (2012), for instance, we analyze the pricing of international stocks. We find that the distribution of international returns can be significantly better explained if conditioning an otherwise standard international asset pricing model on fourth-quarter growth in G-7 industrial production. In future work, we intend to examine further the interesting relationship that exist between economic growth at the end of the year and financial markets.

References

Abel, A.B., Eberly, J.C., Panageas, S., 2007. Optimal inattention to the stock market. *American Economic Review* 97, 244-249.

Abel, A.B., Eberly, J.C., Panageas, S., 2011. Optimal inattention to the stock market in the presense of transactions costs. *Working paper*, University of Pennsylvania, Northwestern University, University of Chicago.

Amihud, Y., Hurvich, C. M., 2004. Predictive regressions: A reduced-bias estimation method. *Journal of Financial and Quantitative Analysis* 39, 813-841.

Amihud, Y., Hurvich, C. M., Wang, Yi, 2009. Multiple-predictor regressions: Hypothesis testing. *Review of Financial Studies* 22, 413-434.

Bacchetta, P., van Wincoop, E., 2010. Infrequent portfolio decisions: A solution to the forward discount puzzle. *American Economic Review* 100, 870-904.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 56, 1645-1680.

Barsky, R.B., Miron, J.A., 1989. The seasonal cycle and the business cycle. *Journal of Political Economy* 97, 503-534.

Beaulieu, J.J., Miron, J.A., 1992. A cross country comparison of seasonal cycles and business cycles. *Economic Journal* 102, 772-788.

Beaulieu, J.J., MacKie-Mason, J., Miron, J.A., 1992. Why do countries and industries with large seasonal cycles also have large business cycles? *Quarterly Journal of Economics* 107, 621-656.

Bekaert, G., Engstrom, E., Grenadier, S., 2010. Stock and Bond Returns with Moody Investors. *Journal of Empirical Finance* 17, 867-894.

Belo, F., Yu, J., 2012. Government investment and the stock market. Manuscript, *University of Minnesota.*

Boudoukh, J., Richardson, M., Whitelaw, R., 2008. The myth of long-horizon predictability. *Review of Financial Studies* 21, 1577-1605.

Braun, R.A. and C.L. Evans, 1995. Seasonality and equilibrium business cycle theories. *Journal of Economic Dynamics and Control* 19, 503-531.

Brav, A., Constantinides, G., Geczy, C., 2002. Asset pricing with heterogeneous consumers and limited participation: Empirical evidence. *Journal of Political Economy* 110, 793–824.

Brown, G.W., Cliff, M.T., 2005. Investor sentiment and asset valuation. *Journal of Business* 78, 405-440.

Campbell, J.Y., 1987. Stock returns and the term structure. *Journal of Financial Economics* 18, 373-399.

Campbell, J.Y., 2003. Consumption-based asset pricing. In: Constantinides, G., Harris, M., Stulz, R., *Handbook of the Economics of Finance*, North Holland, Amsterdam, 803-887.

Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: A consumption based explanation of aggregate stock market behavior. *Journal of Political Economy* 107, 205-251.

Campbell, J.Y., Shiller, R., 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1, 195-208.

Charoenrook, A., 2003. Does sentiment matter? *Manuscript*, Vanderbilt University.

Clark, T.E., McCracken, M.W., 2001. Tests of forecast accuracy and encompassing for nested models. *Journal of Econometrics* 105, 85-110.

Clark, T.E., West, K.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138, 291-311.

Cochrane, J.H., 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance* 46, 209-237.

Cochrane, J., 2007. Financial markets and the real economy. In: Mehra, R., *Handbook of the Equity Premium*, North Holland, Amsterdam, 237-325.

Cochrane, J., Piazzesi, M., 2005. Bond risk premia. *Journal of Political Economy* 95, 138-160.

Cooper, I., Priestley, R., 2009. Time-varying risk premiums and the output gap. *Review of Financial Studies* 22, 2801-2833.

Da, Z., Yun, H., 2010. Electricity consumption and asset prices. *Manuscript*, University of Notre Dame.

Duffie, D., Sun, T.-S., 1990. Transactions costs and portfolio choice in a discrete-continuous time setting. *Journal of Economic Dynamics and Control* 14, 35-51.

Fama, E.F., French, K.R., 1988. Dividend yields and expected stock returns. *Journal of Financial Economics* 22, 3-25.

Fama, E.F., French, K.R., 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23-49.

Ferson, W.E. and C.R. Harvey, 1992. Seasonality and consumption-based asset pricing. *Journal of Finance* 47, 511-552.

Fisher, K.L., Statman, M., 2003. Consumer confidence and stock returns. *Journal of Portfolio Management*, 115-127.

Goyal, A., Welch, I., 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21, 1455-1508.

Guo, H., 2009. Data revisions and out-of-sample stock return predictability. *Economic Inquiry* 47, 81-97.

He, J, Ng, L, Wang, Q, 2004. Quarterly trading patterns of financial institutions. Journal of Business 77, 493-509.

Henkel, S.J., Martin, J.S., Nardari, F., 2011. Time-varying short-horizon predictability. *Journal of Financial Economics* 99, 560-580.

Jagannathan, R., Wang, Y., 2007. Lazy investors, discretionary consumption, and the cross-section of stock returns. *Journal of Finance* 62, 1623-1661.

Jagannathan, R., Marakani, S., Takehara, H, Wang, Y., 2012. Calendar cycles, infrequent decisions, and the cross section of stock returns. *Management Science* 58, 507-522.

Kamstra, M., Kramer, L., Levi, M., Wang, T., 2011. Seasonally Varying Preferences: Theoretical Foundations for an Empirical Regularity. *Working Paper* University of Toronto.

Lamont, O.A., 2000. Investment plans and stock returns. *Journal of Finance* 55, 2719-2745.

Lemmon, M., Portniaguina, E., 2006. Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies* 19, 1499-1529.

Lettau, M., Ludvigson, S., 2001. Consumption, aggregate wealth and expected returns. *Journal of Finance* 55, 815-849.

Lettau, M., Ludvigson, S., 2010. Measuring and modeling variation in the risk-return tradeoff. *Handbook of Financial Econometrics* vol. 1, 617-690.

Ludvigson, S., 2011. Advances in consumption-based asset pricing: Empirical tests. Forthcoming in Volume 2 of the *Handbook of the Economics of Finance.*

Ludvigson, S., 2004. Consumer confidence and consumer spending. *Journal of Economic Perspectives* 18, 29-50

Lustig, H., Van Nieuwerburgh, S., 2005. Housing collateral, consumption insurance and risk premia: An empirical perspective. *Journal of Finance* 60, 1167-1219.

Lynch, A., 1996. Decision frequency and synchronization across agents: Implications for aggregate consumption and equity return. *Journal of Finance* 51, 1479-1497.

McCracken, M.W., 2007. Asymptotics for out-of-sample tests of causality. *Journal of Econometrics* 140, 719-752.

Malloy, C.J., Moskowitz, T.J., Vissing-Jørgensen, A., 2009. Long-run stockholder consumption risk and asset returns. *Journal of Finance* 64, 2427-2479.

Miron, J.A., 1986. Seasonal uctuations and the life cycle-permanent income model of consumption. *Journal of Political Economy* 94, 1258-1279.

Møller, S.V., 2008. Consumption growth and time-varying expected returns. *Finance Research Letters* 5, 129-136.

Møller, S.V., Rangvid, J., 2012. End-of-the-year growth in the world-economy and the cross-section of international returns. *Manuscript*, Copenhagen Business School

Newey, W.K., West, K.D., 1987. A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703-708.

Qui, L., Welch, I., 2006. Investor sentiment measures. *Manuscript*, Brown University.

Rangvid, J., 2006. Output and expected returns. *Journal of Financial Economics* 81, 595-624.

Rapach, D.E., Zhou, G., 2011. Forecasting stock returns. Working Paper in preparation for G. Elliott and A. Timmermann, Eds., *Handbook of Economic Forecasting* Volume 2.

Rapach, D.E., Strauss, J.K., Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies* 23, 821-868.

Ritter, J.R, Chopra, N, 1989. Portfolio rebalancing and the turn-of-the-year effect. *Journal of Finance* 44, 149-166.

Santos, T., Veronesi, P., 2006. Labor income and predictable stock returns. *Review of Financial Studies* 19, 1-44.

Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance* 16, 394-408.

Stambaugh, R.F., 1999. Predictive regressions. *Journal of Financial Economics* 54, 375-421.

Valkanov, R.I., 2003. Long-horizon regressions: Theoretical results and applications. *Journal of Financial Economics* 68, 201-232.

Wachter, J.A., Yogo, M., 2010. Why do household portfolio shares rise in wealth? *Review of Financial Studies* 23, 3929-3965.

Wen, Y., 2002. The business cycle effect of Christmas. *Journal of Monetary Economics* 49, 1289-1314.

Table 1. Summary statistics of quarterly growth rates of seasonally-adjusted real macroeconomic variables.

	G^1	G^2	G^3	G^4
	Industrial production			
Mean	0.77%	0.73%	0.71%	0.81%
SD	2.37%	2.01%	1.75%	2.14%
AR1	−0.13	−0.20	−0.28	−0.28
	GDP			
Mean	0.86%	0.88%	0.83%	0.67%
SD	1.22%	0.94%	0.81%	1.01%
AR1	−0.13	0.05	0.09	−0.31
	Consumption			
Mean	0.51%	0.54%	0.46%	0.50%
SD	0.50%	0.49%	0.49%	0.53%
AR1	0.02	−0.05	0.21	0.05

Correlation matrix

	IP	GDP	C
IP	1.00	0.87	0.54
GDP		1.00	0.50
C			1.00

The table reports averages (Mean), standard deviations (SD), and first-order autoregressive coefficients (AR1) of quarterly real GDP growth rates (GDP), real per capita consumption growth rates (C), and industrial production growth rates (IP). The lower part of the table shows the correlations between the fourth-quarter (G^4) growth rates of the different macroeconomic variables.

Table 2. Predictive regressions of one-year-ahead excess stock returns on growth rates of real macroeconomic variables.

	Value-weighted				Equal-weighted		
	G^1	G^2	G^3	G^4		G^4	
Industrial production							
β	-1.22	-1.02	0.72	-3.78		-6.16	
t-value	-1.55	-0.91	0.63	**-5.74**		**-6.16**	
$\bar{R}^2$	0.79%	-0.43%	-1.24%	17.93%		22.42%	
GDP							
β	-2.20	-1.95	2.66	-7.48		-11.78	
t-value	-1.08	-0.97	0.86	**-4.95**		**-4.96**	
$\bar{R}^2$	0.53%	-0.66%	-0.37%	15.40%		17.95%	
Consumption							
β	0.84	-4.26	-3.28	-14.61		-21.98	
t-value	0.20	-1.13	-0.87	**-4.88**		**-5.25**	
$\bar{R}^2$	-1.64%	-0.40%	-0.99%	16.05%		16.93%	
Benchmark variables		DP	TMS	$\widehat{cay}$	DP	TMS	$\widehat{cay}$
β		4.96	1.85	3.87	5.59	2.67	4.15
t-value		**3.07**	1.67	**3.65**	**2.63**	1.67	**2.50**
$\bar{R}^2$		10.82%	0.52%	11.78%	5.66%	0.45%	5.49%

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 and the benchmark variables, 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. The sample period is 1948-2009.

Table 3. Predictive regressions of cumulative long-horizon excess stock returns on quarterly growth rates of industrial production.

		t→t+1	t→t+2	t→t+3	t→t+4	t→t+8	t→t+12
				Value-weighted returns			
$G^{IP,4}$	β	-0.74	-1.79	-2.68	-3.78	-4.24	-3.55
	t-value	-1.46	**-2.40**	**-4.69**	**-5.74**	**-2.42**	-1.80
	$\bar{R}^2$	2.47%	8.40%	11.62%	17.93%	8.55%	3.14%
$G^{IP,3}$	β	0.45	0.63	-0.37	0.72	0.47	1.73
	t-value	0.67	0.63	-0.30	0.63	0.32	1.46
	$\bar{R}^2$	-0.78%	-0.98%	-1.54%	-1.24%	-1.65%	-1.02%
$G^{IP,2}$	β	0.35	-0.15	-0.47	-1.02	0.53	-1.73
	t-value	0.74	-0.18	-0.45	-0.91	0.42	-1.30
	$\bar{R}^2$	-1.06%	-1.64%	-1.32%	-0.43%	-1.57%	-0.78%
$G^{IP,1}$	β	-0.14	-0.11	-0.78	-1.22	-0.21	-0.84
	t-value	-0.33	-0.18	-1.11	-1.55	-0.16	-0.65
	$\bar{R}^2$	-1.52%	-1.66%	-0.28%	0.80%	-1.70%	-1.53%
				Equal-weighted returns			
$G^{IP,4}$	β	-1.40	-3.29	-4.64	-6.16	-7.11	-6.57
	t-value	-1.82	**-2.83**	**-4.76**	**-6.16**	**-2.78**	-1.92
	$\bar{R}^2$	5.29%	14.10%	18.29%	22.43%	11.39%	5.57%

$G^{IP,i}$ is the growth rate of industrial production during quarter $i = 1, 2, 3, 4$. "t→t+1" indicates excess returns during the following quarter, i.e., for $G^{IP,4}$, "t→t+1" indicates predictions of returns during the first quarter of the year, for $G^{IP,3}$, "t→t+1" indicates predictions of returns during the fourth quarter of the year, etc. "t→t+2" indicates cumulative excess returns during the following two quarters, i.e., for $G^{IP,4}$, "t→t+2" indicates predictions of cumulative returns during the first two quarters of the year, for $G^{IP,3}$, "t→t+2" indicates predictions of cumulative returns during the fourth quarter of the year and the first quarter next year, etc. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic.

Table 4. Monthly predictive regressions of one-year ahead excess returns on monthly growth rates in industrial production.

	Value-weighted			Equal-weighted		
	β	t-value	$\bar{R}^2$	β	t-value	$\bar{R}^2$
December	−4.59	**−3.31**	9.10%	−8.24	**−3.58**	14.68%
November	−4.16	**−2.63**	5.87%	−5.80	**−2.50**	5.75%
October	−3.50	**−2.05**	2.05%	−5.15	**−2.23**	2.38%
September	−2.70	−1.26	0.50%	−4.36	**−2.15**	1.68%
August	0.29	0.18	−1.65%	−1.13	−0.62	−1.28%
July	2.68	1.31	0.20%	2.33	0.83	−0.80%
June	−0.69	−0.19	−1.62%	−2.14	−0.43	−1.25%
May	−2.06	−0.75	−0.75%	−5.97	−1.47	2.56%
April	−2.21	−0.86	−0.20%	−4.90	−1.31	2.17%
March	−1.93	−0.69	−0.83%	−4.42	−1.07	0.70%
Februar	−2.56	−0.91	0.00%	−6.66	−1.89	4.08%
Januar	−0.06	−0.04	−1.69%	−2.17	−1.01	−0.79%

When using December growth rates to predict, the one-year ahead excess return is measured from the beginning of January to the end of December; when using November growth rates to predict, the one-year ahead excess return is measured from the beginning of December to the end of November next year; etc. The sample period is 1948-2009.

Table 5. Out-of-sample regressions of one-year-ahead excess stock returns on the fourth-quarter growth rate of economic variables.

	Value-weighted				Equal-weighted			
	OOS R^2	ENC	$MSE\text{-}F$	$t(NW)$	OOS R^2	ENC	$MSE\text{-}F$	$t(NW)$
Q4 variables. Now available data								
Indu. prod.	10.87%	**3.75**	**4.27**	1.60	19.59%	**6.05**	**8.52**	**2.06**
GDP	12.57%	**3.65**	**5.03**	**1.79**	19.75%	**5.66**	**8.61**	**2.24**
Consump.	9.75%	**3.35**	**3.78**	**2.16**	12.49%	**3.77**	**5.00**	**2.32**
Q4 variables. Vintage data								
Indu. prod.	12.33%	**4.24**	**4.92**	1.58	20.74%	**6.56**	**9.16**	**2.16**
Consump.	9.38%	**2.83**	**3.62**	**1.73**	9.86%	**2.90**	**3.83**	1.33
Benchmark variables								
DP	−4.18%	1.56	−1.40	0.79	−2.76%	1.15	−0.94	0.93
TMS	−7.05%	−0.66	−2.30	−0.85	−6.74%	−0.87	−2.21	−1.26
$\widehat{cay}$	2.66%	**3.53**	0.96	**2.37**	−2.25%	0.89	−0.77	1.11

$ENC\text{-}NEW$ is the forecast encompassing test of Clark & McCracken (2001). $MSE\text{-}F$ is the equal forecast accuracy test of McCracken (2007). $t(NW)$ is the adjusted test in Clark & West (2007). Asymptotic critical values at the 5% significance level are 1.85 for the $ENC\text{-}NEW$ test, 1.62 for the $MSE\text{-}F$ test, and 1.65 for the $t(NW)$ test. OOS R^2 is the unconstrained Campbell & Thompson (2008) out-of-sample R^2-statistic. 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 6. Subsample analyses using 4th-quarter variables and benchmark variables

		1948-1979		1980-2009		1980-2007	
		EW	VW	EW	VW	EW	VW
IP	β	-6.90	-4.41	-7.92	-2.44	-6.59	-1.86
	t-value	**-5.06**	**-6.41**	**-4.75**	-1.56	**-4.11**	-0.87
	$\bar{R}^2$	24.76%	32.55%	20.73%	1.30%	13.44%	-1.07%
GDP	β	-10.20	-8.17	-14.95	-5.99	-11.84	-5.05
	t-value	**-3.54**	**-4.09**	**-3.58**	**-2.65**	**-3.17**	**-2.13**
	$\bar{R}^2$	15.10%	22.46%	19.61%	4.30%	13.17%	2.41%
C	β	-21.89	-17.10	-23.63	-10.53	-24.54	-14.37
	t-value	**-4.13**	**-4.82**	**-3.15**	**-2.01**	**-3.64**	**-3.43**
	$\bar{R}^2$	19.01%	26.35%	12.98%	3.40%	17.36%	10.86%
AVE	β	-11.24	-8.72	-15.08	-5.32	-13.49	-5.09
	t-value	**-5.08**	**-6.47**	**-5.48**	**-2.48**	**-4.77**	-1.87
	$\bar{R}^2$	25.57%	34.59%	23.16%	3.48%	18.29%	2.53%
Benchmark variables							
$\widehat{cay}$	β	8.89	6.84	2.37	2.68	1.80	2.81
	t-value	**2.57**	**3.33**	1.60	**2.20**	1.33	**2.43**
	$\bar{R}^2$	20.10%	26.89%	-0.90%	3.90%	-1.52%	7.62%
DP	β	10.18	8.90	2.14	3.18	0.32	1.93
	t-value	**2.42**	**3.94**	0.75	1.22	0.15	0.80
	$\bar{R}^2$	14.80%	25.54%	-2.65%	0.72%	-3.82%	-1.62%
TMS	β	4.16	3.49	3.31	3.07	2.39	1.44
	t-value	1.11	0.88	1.71	**2.64**	1.49	1.33
	$\bar{R}^2$	0.12%	-0.63%	1.64%	4.42%	0.16%	-0.90%

IP is industrial production and C consumption. The macroeconomic growth rates are all fourth-quarter growth rates. AVE is the average of IP, GDP, and C. VW is the value-weighted portfolio whereas EW is the equal-weighted portfolio.

Table 7. International evidence on excess return predictability by global fourth-quarter growth rates of industrial production.

	G7 growth rates					Equal weighted growth rates			
	G^1	G^2	G^3	G^4		G^1	G^2	G^3	G^4
	World					World			
β	−0.87	−1.63	−0.77	−3.29	β	−1.60	−1.31	−3.31	−3.78
t-value	−0.91	−0.74	−0.26	**−3.20**	t-value	−0.75	−0.79	−0.93	**−3.90**
$\bar{R}^2$	−2.34%	−1.59%	−2.54%	6.63%	$\bar{R}^2$	−2.09%	−2.01%	−0.54%	8.61%
	World ex US					World ex US			
β	1.18	−0.44	−0.74	−3.44	β	−0.84	−0.68	−3.12	−4.54
t-value	1.06	−0.20	−0.26	**−3.86**	t-value	−0.32	−0.33	−0.95	**−5.43**
$\bar{R}^2$	−2.29%	−2.65%	−2.60%	4.38%	$\bar{R}^2$	−2.60%	−2.58%	−1.31%	8.61%
	Europe, Australia and the Far East					Europe, Australia and the Far East			
β	0.99	−0.54	−1.02	−3.55	β	−0.36	−0.92	−3.71	−4.75
t-value	0.88	−0.26	−0.37	**−3.37**	t-value	−0.13	−0.47	−1.11	**−5.02**
$\bar{R}^2$	−2.42%	−2.62%	−2.51%	4.40%	$\bar{R}^2$	−2.68%	−2.48%	−0.80%	8.97%
	Europe					Europe			
β	0.49	1.89	1.04	−3.83	β	0.22	1.78	−1.50	−4.51
t-value	0.41	0.68	0.30	**−3.29**	t-value	0.07	0.70	−0.42	**−4.18**
$\bar{R}^2$	−2.63%	−1.75%	−2.45%	5.98%	$\bar{R}^2$	−2.70%	−1.88%	−2.31%	8.33%

The table shows results from regressions of calendar year returns in different regions on the lag of fourth-quarter growth rates of industrial production. Returns are excess returns in US dollars from the MSCI World, MSCI World ex US, MSCI EAFE, and MSCI Europe. In the left-hand panel, the fourth-quarter growth rates of G7 industrial production is used as predictive variable. In the right-hand panel, an equal-weighted Q4 growth rate of industrial production in Australia, Belgium, France, Germany, Japan, Italy, Netherlands, Sweden, Switzerland, UK and US is used. The sample period is 1970-2009. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic.

Table 8. Predictive regressions of one-year-ahead excess returns from a two-year bond on growth rates of real macroeconomic variables.

	G^1	G^2	G^3	G^4
	Industrial production			
β	-0.12	0.02	-0.13	-0.27
t-value	-1.11	0.11	-0.94	$\mathbf{-2.92}$
$\bar{R}^2$	0.29%	-1.82%	-0.73%	9.25%
	GDP			
β	-0.29	0.09	-0.26	-0.45
t-value	-1.18	0.25	-0.90	$\mathbf{-2.22}$
$\bar{R}^2$	1.68%	-1.65%	-0.43%	4.71%
	Consumption			
β	-0.59	0.26	-1.28	-0.80
t-value	-1.31	0.30	$\mathbf{-2.45}$	$\mathbf{-2.61}$
$\bar{R}^2$	0.59%	-1.46%	7.95%	4.05%

For G^1, the one-year-ahead excess bond 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 bond 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 bond return is measured from the beginning of the fourth quarter to the end of the third quarter next year. For G^4, the one-year-ahead excess bond 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. The sample period is 1953-2009.

Table 9. Quarterly growth rates of consumer confidence and purchasing managers index regressed on quarterly growth rates of industrial production.

	G^1	G^2	G^3	G^4	G^1	G^2	G^3	G^4
	Consumer confidence							
	University of Michigan				Conference Board			
β	0.83	0.17	−0.47	1.33	2.51	0.62	0.87	5.29
t-value	**2.18**	0.16	−0.55	**3.19**	**1.99**	0.22	0.56	**7.91**
$\bar{R}^2$	5.55%	−2.00%	−1.04%	13.59%	17.04%	−2.18%	−1.03%	55.54%
	Purchasing managers index							
	Composite PMI index				Production index			
β	1.55	1.64	1.87	2.74	1.13	1.25	1.52	3.18
t-value	**3.68**	1.91	1.87	**4.71**	**2.60**	1.14	1.33	**4.40**
$\bar{R}^2$	18.48%	7.39%	6.54%	41.61%	7.00%	2.27%	2.84%	40.60%

We run contemporaneous regressions of quarterly growth rates in confidence on quarterly growth rates in industrial production. G^i refers to the growth in industrial production in quarter $i = 1$, 2, 3, and 4. We use G^1 as explanatory variable for the first-quarter growth rate in consumer confidence/PMI (i.e., the change in the index between the fourth and first quarter). Similarly, we use G^2 as explanatory variable for the change between the first and second quarter, G^3 as explanatory variable for the change between the second and third quarter, and, finally, G^4 as explanatory variable for the change in confidence/PMI between the third and fourth quarter. For each regression, the table reports the slope estimate, the Newey-West corrected t-value, and the adjusted R^2-statistic. The sample period is 1961-2009 when analyzing consumer confidence and 1948-2009 when analyzing the PMI.

Table 10. Growth in consumer confidence/PMI and expected returns.

	Value-weighted returns				Equal-weighted returns			
	G^1	G^2	G^3	G^4	G^1	G^2	G^3	G^4
Consumer confidence								
				Conference board				
β	0.90	0.12	−0.49	−0.35	−0.19	0.04	−0.82	−0.96
t-value	0.27	0.54	−1.64	**−2.06**	−0.37	0.12	**−2.01**	**−3.93**
$\bar{R}^2$	−2.31%	−1.75%	1.86%	2.69%	−2.01%	−2.50%	4.28%	15.62%
				University of Michigan				
β	0.44	0.31	−0.62	−0.65	0.20	0.30	−0.89	−1.38
t-value	0.93	0.64	−1.61	−1.60	0.27	0.41	−1.85	**−2.54**
$\bar{R}^2$	−0.35%	−1.03%	0.53%	2.00%	−2.34%	−1.80%	1.01%	6.85%
Purchasing managers index								
				Composite PMI				
β	0.01	−0.00	0.06	−0.84	−0.09	−0.08	0.96	−1.43
t-value	0.04	−0.01	0.03	**−4.01**	−0.31	−0.27	0.33	**−4.20**
$\bar{R}^2$	−1.72%	−1.72%	−1.59%	14.55%	−1.63%	−1.59%	−1.60%	20.85%
				Production index				
β	0.05	0.00	0.02	−0.61	0.01	−0.01	0.01	−1.09
t-value	0.20	0.01	0.12	**−3.69**	0.02	−0.05	0.04	**−4.48**
$\bar{R}^2$	−1.67%	−1.72%	−1.70%	10.46%	−1.72%	−1.72%	−1.72%	16.61%

One-year ahead excess returns on the value-weighted portfolio and the equal-weighted portfolio regressed on growth in consumer confidence or PMI. G^i refers to the growth in the index in quarter i = 1, 2, 3, and 4. The timing is such that 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, and so on for the other quarters (see also notes to Table 2).

Table 11. One-year ahead excess returns (VW) and changes in confidence (Chicago Board) regressed on changes in macro variables.

LHS variable:	**1-year ahead stock returns**				**Confidence growth**			
	G^1	G^2	G^3	G^4	G^1	G^2	G^3	G^4
				Change in output gap, CBO measure				
β	−0.02	−0.01	0.07	−0.10	0.08	0.03	0.02	0.11
t-value	−0.42	−0.36	1.39	**−4.11**	**4.25**	0.47	0.92	**4.75**
$\bar{R}^2$	−1.16%	−1.61%	1.38%	9.24%	23.81%	−1.71%	−0.51%	40.10%
				Change in investment-capital ratio				
β	−33.8	−15.6	−26.2	−53.5	14.7	27.5	23.4	87.5
t-value	−1.85	−0.67	−0.79	**−2.13**	1.04	0.96	1.43	**5.55**
$\bar{R}^2$	1.88%	−0.95%	−0.27%	5.17%	−1.21%	1.08%	0.88%	39.54%
				Change in housing-collateral ratio (residential fixed assets)				
β	5.31	−2.12	1.91	9.51	1.57	−0.24	−3.25	−4.90
t-value	1.46	−0.72	0.47	**2.75**	0.70	−0.13	−1.33	**−2.30**
$\bar{R}^2$	2.79%	−1.16%	−1.53%	14.28%	−0.74%	−2.82%	3.86%	6.84%
				Employment growth (nonfarm)				
β	−6.98	−5.15	−2.73	−11.05	5.65	−6.96	−0.44	14.37
t-value	**−3.07**	−1.36	−0.66	**−3.80**	1.67	−1.16	−0.13	**6.02**
$\bar{R}^2$	6.59%	2.09%	−0.95%	14.83%	8.19%	3.78%	−2.43%	46.12%
				Labor income growth (defined as in Lettau and Ludvigson)				
β	−3.88	1.39	−5.94	−8.43	1.67	3.20	−0.30	8.02
t-value	−1.53	0.81	−1.72	**−3.35**	0.71	1.50	−0.20	**3.53**
$\bar{R}^2$	2.56%	−1.31%	5.09%	11.21%	−0.40%	1.37%	−2.41%	22.71%
				Change in capacity utilization				
β	−0.03	−0.03	0.02	−0.05	0.03	0.02	0.01	0.06
t-value	**−3.30**	−1.16	0.44	**−2.90**	**2.02**	0.60	0.52	**7.77**
$\bar{R}^2$	1.97%	−0.28	−2.01%	8.81%	16.33%	−0.56%	−1.17%	51.93%
				Nonresidential investment growth				
β	−1.33	−0.68	−1.05	−2.24	1.10	0.28	0.59	3.33
t-value	**−2.28**	−0.84	−0.98	**−3.17**	1.74	0.23	1.09	**5.71**
$\bar{R}^2$	2.93%	−0.61%	0.39%	8.31%	5.64%	−2.30%	−0.78%	45.27%

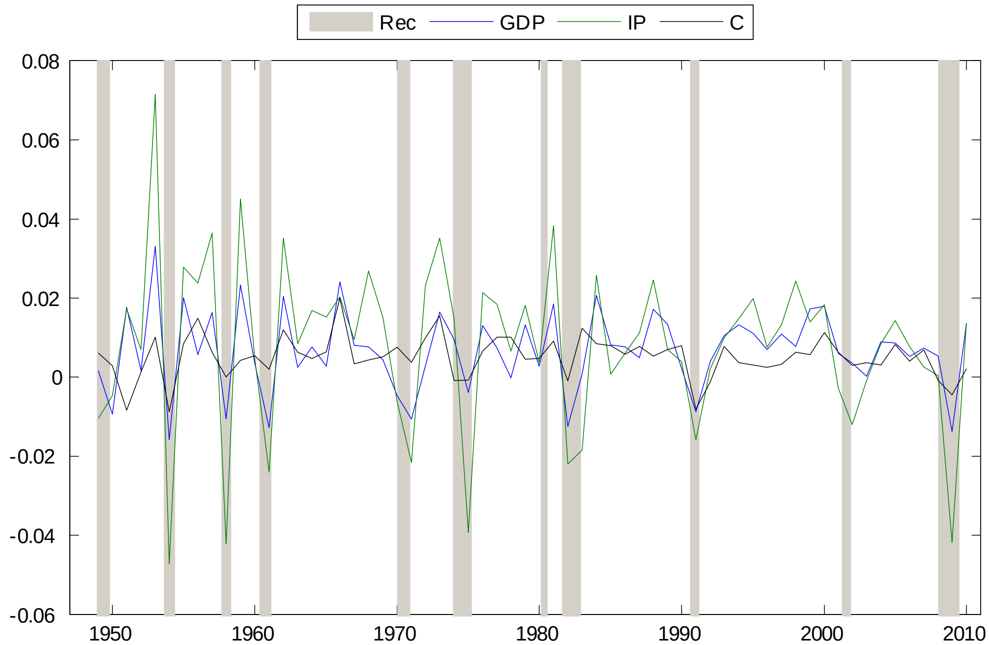
Table 12. Book-to-market and dividend-yield portfolios regressed on fourth-quarter industrial production and investor sentiment.

	1	2	3	4	5	6	7	8	9	10	10-1
Book-to-market portfolios											
					Q4 growth in industrial production						
β	-5.94	-5.40	-5.81	-5.77	-5.88	-5.42	-5.70	-6.04	-6.37	-7.88	-1.94
t-value	**-4.47**	**-4.72**	**-5.19**	**-5.32**	**-6.33**	**-6.29**	**-6.71**	**-6.58**	**-6.51**	**-6.35**	**-2.16**
$\bar{R}^2$	15.7%	18.8%	23.6%	23.1%	25.3%	21.5%	23.0%	22.7%	22.8%	22.0%	2.3%
					Baker-Wurgler index						
β	-0.13	-0.10	-0.09	-0.08	-0.08	-0.07	-0.07	-0.08	-0.08	-0.11	0.02
t-value	**-4.76**	**-3.87**	**-3.19**	**-2.81**	**-2.75**	**-2.46**	**-2.44**	**-2.50**	**-2.49**	**-2.95**	0.64
$\bar{R}^2$	13.3%	11.2%	9.3%	8.2%	7.7%	6.8%	6.9%	7.7%	7.2%	7.3%	-1.5%

	No-dividend	1	2	3	4	5	6	7	8	9	10	0-10
Dividend-yield portfolios												
						Q4 growth in industrial production						
β	-8.45	-5.32	-4.86	-4.58	-4.65	-4.60	-4.76	-4.65	-4.88	-4.62	-5.42	-3.03
t-value	**-6.14**	**-5.91**	**-5.55**	**-4.90**	**-5.84**	**-5.60**	**-5.47**	**-5.92**	**-6.57**	**-6.16**	**-6.70**	**-3.60**
$\bar{R}^2$	19.8%	18.5%	19.8%	18.1%	19.8%	20.1%	21.3%	21.0%	22.8%	21.9%	25.4%	4.9%
							Baker-Wurgler index					
β	-0.17	-0.08	-0.08	-0.07	-0.06	-0.06	-0.05	-0.04	-0.03	-0.03	-0.03	-0.14
t-value	**-4.45**	**-3.05**	**-3.04**	**-2.31**	**-2.11**	-1.92	-1.62	-1.26	-1.06	-1.13	-0.81	**-4.17**
$\bar{R}^2$	16.3%	9.7%	11.0%	6.5%	5.4%	4.2%	3.1%	1.2%	0.0%	0.6%	-0.8%	24.6%

The portfolio returns are measured over the calendar year. The portfolio returns are regressed on either the fourth-quarter growth in industrial production (1948-2009) or the Baker-Wurgler investor sentiment index (1965-2009).

Figure 1: The fourth-quarter growth rate of macroeconomic time series together with NBER recessions.



Research Papers 2012

CREATES
Center for Research in Econometric Analysis of Time Series