Consumption Fluctuations and Expected Returns

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Abstract

This paper introduces a novel consumption-based variable, cyclical consumption, and examines its predictive properties for stock returns. Future expected stock returns are high (low) when aggregate consumption falls (rises) relative to its trend and marginal utility from current consumption is high (low). We show that the empirical evidence ties consumption decisions of agents to time-variation in returns in a manner consistent with asset pricing models based on external habit formation. The predictive power of cyclical consumption is not confined to bad times and subsumes the predictability of many popular forecasting variables.

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In this paper, we take a new approach to linking stock return predictability to both bad and good economic times. Consider an economy in which investors exhibit external habit formation as in, for example, Campbell and Cochrane (1999), and as a result risk premia vary over time through variation in risk aversion. In good times, when consumption rises above its trend and hence the marginal utility of present consumption is low, investors are willing to give up current consumption and invest. This in turn forces stock prices to increase and future expected returns to decrease. Conversely, in bad times, when consumption falls below its trend and hence the marginal utility of current consumption is high, expected returns in the future need to be high in order to induce investors to postpone the valuable present consumption and to invest and consume in the future. We conjecture that cyclical fluctuations in aggregate consumption should be useful in picking out bad and good times in the economy as measured from a representative agent's point of view, and thus informative about future excess stock returns. If this argument holds, then we should find an inverse relation between cyclical consumption and future expected returns in the data.

The empirical results that we present in this paper are consistent with the idea that future expected returns are high (low) when consumption falls below (rises above) its trend and cyclical consumption is low (high). Cyclical fluctuations in consumption, which we refer to as cc, capture a significant fraction of the variation in future stock market returns. The finding that expected returns and consumption are linked is important because it suggests that asset prices are driven by fundamental shocks that reflect changes in marginal utility.

A second notable finding in this paper is that the predictive power of cyclical consumption is not confined to bad times alone. Cyclical consumption provides a consistent description of how both positive and negative macroeconomic events, as reflected by investors' consumption decisions, affect stock market returns. This finding stands in stark contrast to Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018), who document that popular predictive variables can forecast stock returns in bad times, but find essentially no evidence of predictability during business cycle expansions.

To extract the cyclical component of consumption, we employ the simple and robust linear projection method of Hamilton (2018). This procedure provides a measure of what macroeconomists often refer to as the "cyclical component" of a time series and it has two advantages over other prominent detrending methods. First, the procedure ensures that the cyclical component that is identified is stationary and consistently estimated for a wide range of nonstationary processes. Second, it produces a series that is accurately related to the underlying economic fluctuations, as opposed to, for instance, the popular Hodrick and Prescott (1997) filter, which can spuriously generate dynamic relations. This feature of the Hamilton (2018) detrending procedure is particularly appealing because it implies that any predictive ability of cyclical consumption for stock returns is more likely to reflect actual predictability than to be a statistical artifact of the decomposition method. When we employ other econometric procedures to isolate the cyclical variation in consumption, such as polynomial time trends and backward-looking moving averages, we find even stronger evidence of predictability. We therefore view Hamilton's (2018) detrending procedure as providing conservative and robust evidence on return predictability.

Our findings support theoretical explanations of asset prices that generate time-varying expected returns, such as models with time-varying risk aversion. In the external habit formation model of Campbell and Cochrane (1999), for example, habit acts like a trend for consumption. A decline in consumption relative to the trend, which can be thought of as bad times, leads to low stock prices and high expected returns. Conversely, an increase in consumption above trend, which can be thought of as good times, leads to high stock prices and low expected returns. Under relatively mild assumptions, there exists a tight relation between a finite-horizon version of the surplus consumption variable of Campbell and Cochrane (1999), which generates changes in equity prices in the model, and cyclical consumption.

To examine the link between cyclical consumption and habit models more formally, we simulate data from the Campbell and Cochrane (1999) model and investigate both the extent of the model-implied predictability and its consistency with the time-series predictability that we observe in actual data. The simulations show that the habit model produces an inverse relation between expected returns and cyclical consumption just as in the data. The degree of in-sample predictability implied by the model is qualitatively comparable to that in the data. The out-of-sample tests reinforce the results from in-sample regressions but typically indicate less predictable movements in expected returns. These findings suggest that our results can be taken as evidence of countercyclical variation in the market price of consumption risk.

We perform a battery of robustness checks and address a number of econometric concerns surrounding predictive regressions with persistent predictors (Nelson and Kim (1993) and Stambaugh (1999)). Both the IVX testing approach of Kostakis, Magdalinos, and Stamatogiannis (2015) that accounts for the degree of regressor persistence and an advanced bootstrap procedure that accounts for the regressor's time-series properties provide strong evidence of predictability at the one-quarter horizon that extends to horizons of up to five years. Moreover, this predictability does not vanish during the post-oil-crisis period, a period in which standard business cycle indicators have proven dismal as predictive variables (Welch and Goyal (2008)).

We also show that the forecasting power of fluctuations in cyclical consumption is not confined to the aggregate U.S. stock market. Robust patterns of predictability exist across industry portfolios. In addition, the strong predictive ability of cyclical consumption extends to international equity markets. A global measure of cyclical consumption computed as the simple average of country-specific components captures a large part of the time-variation in future expected returns on the world market portfolio as well as on regional portfolios such as the European portfolio, the EAFE (Europe, Australia, and the Far East) portfolio, and the G7 portfolio.

Explaining the dynamic behavior of asset returns using aggregate consumption data is a challenging task. Few studies find evidence in favor of returns being predictable from consumption. Perhaps the most prominent consumption-based predictive variable is Lettau and Ludvigson's (2001) consumption-wealth ratio, *cay*. We find that the information content of cyclical consumption is clearly above and beyond that of many well-recognized variables, such as the consumption-wealth ratio of Lettau and Ludvigson (2001), the labor-income-to-consumption ratio of Santos and Veronesi (2006), and the conditional volatility of consumption of Bansal, Khatchatrian, and Yaron (2005). In total, we consider 19 alternative economic variables that are popular in the literature. We find that few of them have predictive power, and none of them can systematically generate better out-of-sample forecasts than cyclical consumption.

While we emphasize the connection between our empirical analysis and the external habit model of Campbell and Cochrane (1999), our result that consumption fluctuations can predict stock returns appears consistent with other classes of asset pricing models such as learning models that can generate countercyclical variation in risk premia (Collin-Dufresne, Johannes, and Lochstoer (2016) and Nagel and Xu (2018)). A series of positive fundamental shocks in a learning model induces the agent to be optimistic, which leads up to high asset prices and in turn low subsequent future returns. For example, Nagel and Xu (2018) predict that the equity premium is negatively related to long-run weighted averages of past real per capita payout growth rates and they verify this empirically. Thus, in line with our empirical results, past growth rates of fundamentals generate slow-moving time-variation in expected returns. However, unlike the habit-based explanation of return predictability, the learning model of Nagel and Xu (2018) features constant relative risk aversion and return predictability that is induced by subjective belief dynamics rather than time-varying risk aversion.

Other models could also be congruous with our empirical finding that consumption fluctuations can predict future stock returns. For example, models with heterogeneous investors such as Constantinides and Duffie (1996) and Constantinides and Ghosh (2017) can generate a link between past fundamentals and expected market returns. In these models, countercyclical shocks to labor income risk imply countercyclical variation in the equity premium and hence in stock return behavior that could be reflected in consumption fluctuations. Similarly, Chien, Cole, and Lustig (2016) show that in a model in which agents have different asset trading technologies, a sequence of bad shocks can magnify cyclical fluctuations in the price of risk and drive up the Sharpe ratio.

Recent models that include leverage offer a direct link whereby countercyclical variation in leverage generates predictability of the risk premium and affects aggregate consumption dynamics. For example, Gomes and Schmid (2017) develop a general equilibrium model with heterogeneous firms in which countercyclical leverage drives up risk premia on financial assets during downturns that is naturally reflected in credit spread changes. Because defaults tend to cluster during downturns, when the market price of risk is high, credit spreads spike up in recessions. These endogenous movements in credit prices amplify the effects of macroeconomic shocks and imply predictable patterns in expected stock returns over the business cycle.

The paper proceeds as follows. In Section I we provide details on the construction of cyclical consumption. In Section II we present our empirical results. We summarize a number of robustness tests in Section III. Section IV examines the out-of-sample forecasting ability across alternative predictors. In Section V we develop a simple economic framework based on the habit model of Campbell and Cochrane (1999) in which cyclical consumption emerges as a relevant predictor variable for future stock returns. Section V also reports simulation results used to compare the predictability in the model to that in the data. Finally, in Section VI we conclude.

I. Extracting Cyclical Consumption

As our primary measure of consumption, we use aggregate seasonally adjusted consumption expenditures on nondurables and services from Table 7.1 of the National Income and Product Accounts (NIPA) constructed by the U.S. Bureau of Economic Analysis (BEA). The data are quarterly, are in real per capita terms, in 2009 chain-weighted dollars, and span the period from 1947Q1 to 2017Q4.

To extract the cyclical component of consumption, we employ the simple and robust linear projection method of Hamilton (2018), which provides an alternative means to identify what macroeconomists usually refer to as the cyclical component of a time series. Specifically, we regress the log of real per capita consumption, c_t, on a constant and four lagged values of consumption as of time $t-k$,

$$c_t = b_0 + b_1 c_{t-k} + b_2 c_{t-k-1} + b_3 c_{t-k-2} + b_4 c_{t-k-3} + \omega_t, \tag{1}$$

where the regression error, ω_t, is our measure of cyclical consumption cc_t at time t:

$$cc_t = c_t - \widehat{b}_0 - \widehat{b}_1 c_{t-k} - \widehat{b}_2 c_{t-k-1} - \widehat{b}_3 c_{t-k-2} - \widehat{b}_4 c_{t-k-3}. \tag{2}$$

This procedure has several attractive features in comparison to other popular detrending methods. In particular, it offers a reasonable model-free way to construct a time series that is accurately related to actual economic fluctuations as opposed to, for instance, the Hodrick and Prescott (1997) filter, which can spuriously generate series with dynamics that have no relation to the underlying data-generating process. Under plausible assumptions, the Hamilton (2018) method ensures that the residual component that is identified is stationary and consistently estimated for a wide range of unknown and possibly nonstationary processes.[1] Furthermore, by virtue of the fact that cc is a one-sided filter, any finding that cyclical

[1] The detrending procedure of Hamilton (2018) allows us to remove the nonstationary component of c_t without modeling the nonstationarity, as the decomposition in equation (1) implies a stationary process ω_t if either the kth difference of c_t or the deviation of c_t from a kth-order deterministic time polynomial is stationary for some k as the sample size becomes large. See Hamilton (2018) for a formal proof.

consumption can predict future observations of some other variable should represent true predictive ability rather than an artifact of the choice of detrending method.[2]

Empirical implementation of equation (1) requires a choice of k. Hamilton (2018) recommends using a two-year horizon as a standard benchmark for business cycle dynamics and horizons of around five years to capture the effect of longer-term shocks that are "nevertheless still transient." We experimented with alternative specifications of k ranging from one to 11 years and generally find evidence of stock return predictability. The benchmark results that we present in the paper are based on computations of cc using a horizon of six years, that is, $k = 24$ in quarterly terms.[3]

[Figure 1 about here]

Figure 1 provides a time-series plot of cc computed from equation (2) for $k = 24$ along with recession dates as defined by NBER. Cyclical consumption has an unconditional mean of zero by construction, a standard deviation of 3.74%, and a first-order autocorrelation of 0.97, which corresponds to a half-life of slightly over five years. This implies highly persistent expected returns in the return forecasting regressions as emphasized by Campbell and Cochrane (1999), Pastor and Stambaugh (2009), and van Binsbergen and Koijen (2010).[4] The figure shows that cc exhibits significant business cycle fluctuations in the post-war period in that it typically rises after recessions and reaches its highest values some time before the onset of recessions, and then falls throughout economic contractions. We argue that these fluctuations in cyclical consumption constitute a more accurate description of good and bad economic times than previously employed predictor variables. If so, cyclical consumption

[2] In this respect, Hamilton (2018) argues that in contrast to the Hodrick-Prescott (1997) cyclical series, which can be readily forecasted from its own lagged values and past values of other variables, by construction the realizations of ω are difficult to predict.

[3] The choice of a six-year horizon turns out to be consistent with implications of the external habit model of Campbell and Cochrane (1999) as we show in Section V.

[4] For comparison, Lettau and Ludvigson (2013) identify a risk aversion shock with a half-life of over four years.

should contain predictive information content about future expected stock returns. We test this hypothesis below.

II. Predictive Regression Analysis

We investigate the forecasting ability of cyclical consumption for two measures of aggregate stock market returns: the return on Standard and Poor's composite stock price index (S&P 500) and the return on the Center for Research in Security Prices (CRSP) value-weighted index of U.S. stocks listed on the NYSE, NASDAQ, and Amex. We compute excess returns by subtracting the return on the 30-day Treasury bill from the market return. We focus on excess returns, but we also examine nominal returns and real returns calculated by deflating nominal returns using the inflation rate of the aggregate U.S. Consumer Price Index (CPI). We download data on returns from the Wharton Research Data Services (WRDS) database and on the CPI inflation rate from the Bureau of Labor Statistics (BLS). Unless otherwise specified, we compute cyclical consumption from the most recently available figures for seasonally adjusted consumption of nondurables and services in real per capita terms and based on the full-sample parameter estimates from equation (2).

A. Return Predictive Regressions

We consider a standard predictive regression model for analyzing aggregate stock return predictability:

$$r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}, \tag{3}$$

where cc_t is one-quarter-lagged cyclical consumption and $r_{t,t+h}$ is the h-quarter-ahead log excess return on the stock market. We measure $r_{t,t+h}$ as the h-quarter continuously compounded log return on the market less the corresponding h-quarter continuously compounded log Treasury bill return.

To test the significance of β in equation (3), we use the Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistic truncated at lag h (our results are robust using other truncation lags). We compute empirical p-values for the slope estimates from a wild bootstrap procedure that accounts for the persistence in regressors and correlations between equity stock return and predictor innovations and that allows for general forms of heteroskedasticity.[5] This simulation produces an empirical distribution that better approximates the finite-sample distribution of the slope estimates in equation (3). For more powerful tests, we follow the recommendation of Inoue and Kilian (2004) and calculate p-values for a one-sided alternative hypothesis.[6]

[Table I about here]

Panel A of Table I reports the OLS estimates of β, the corresponding t-statistics, and the adjusted R^2s, $\bar{R}^2$, from predictive regressions in equation (3). We find that the estimated coefficient on cc_t is negative and that cyclical consumption has an economically sizable predictive effect on future excess stock market returns. In particular, the point estimate of β in the quarterly regression on the S&P 500 index is -1.70 in annual terms (first row, second column in Table I). This implies that a one-standard-deviation decrease in cyclical consumption leads to an increase in the expected return of about six percentage points at an annual rate. The coefficient estimate is strongly statistically significant and the associated $\bar{R}^2$ is 3.69%. Thus, expected returns are low when cyclical consumption is high in good times (i.e., during economic upswings) and are high when cyclical consumption is low in bad times (i.e., during economic downturns). This result is consistent with investors responding rationally to countercyclical variation in the price of consumption risk over time: a decline

[5] A general concern with predictability regressions is that their reliability can be undermined by uncertainty regarding the order of integration of the predictor variable. Statistical inference can be unreliable when the predictor variable is persistent and its innovations are highly correlated with returns (Nelson and Kim (1993) and Stambaugh (1999)). Modelling the predictive variables as local-to-unity processes can lead to invalid inference if the regressor contains stationary or near-stationary components (Valkanov (2003), Lewellen (2004), Campbell and Yogo (2006), and Hjalmarsson (2011)).

[6] The bootstrap procedure we apply follows that of Rapach, Ringgenberg, and Zhou (2016).

in consumption relative to its prior history indicates bad economic times where marginal utility of current consumption is high and future returns are expected to be high.

Columns (3) to (7) in Panel A of Table I show that predictability extends to longer horizons of one to five years. The extent of predictability increases with the horizon in terms of both the size of the estimated coefficient and the $\bar{R}^2$ statistic, but at a decreasing rate. For example, at the four-quarter horizon the estimated coefficient and $\bar{R}^2$ are almost four times as large as those recorded at the one-quarter horizon. In contrast, the increase from the 16- to the 20-quarter horizon is around 25% in terms of the size of the coefficient and less than 10% in terms of the $\bar{R}^2$.[7]

The second row in Panel A of Table I reveals a similar predictability pattern for CRSP value-weighted returns. The table also shows that the predictive power of cyclical consumption applies to both real returns (Panel B) and actual returns (Panel C), although evidence of predictability for actual returns is not quite as pronounced.

[Table II about here]

Kostakis, Magdalinos, and Stamatogiannis (2015) develop a test that is robust to the regressor's degree of persistence (including unit root, local-to-unit root, near-stationary, or stationary persistence classes) and that has good size and power properties. This approach alleviates concerns about the quality of inference under possible misspecification of the (generally unobservable) time-series properties of the regressor in long-horizon predictive regressions. Table II reports results using their IVX estimator to test the significance of the estimate of β in equation (3). We find that the null hypothesis of no predictability can be rejected at the 5% level for excess returns and real returns at all horizons and for both the

[7]Following the advice of an anonymous referee, we compared the direct regression coefficients in Table I with coefficients implied from a first-order VAR model. Table IAIII in the Internet Appendix shows that the indirect coefficients are very similar to the direct coefficients that we obtain from the time-overlapping multi-horizon regressions. The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

CRSP and S&P 500 indices. For actual returns, we obtain slightly lower IVX-Wald statistics but we typically reject the null hypothesis of no predictability.

In summary, we show that stock returns can be predicted in part by cyclical consumption fluctuations at various horizons over the post-war period. Expected returns are predicted to be high when consumption falls relative to its trend, that is, when cyclical consumption is low and marginal utility is high. In bad times when the marginal utility of consumption is high, investors want to consume more and therefore require a higher expected return to give up valuable current consumption. In good times, the marginal utility of consumption is low and investors are inclined to save by investing in stocks, which drives prices up and expected returns down. These findings constitute new evidence of time-varying risk premia that link stock return predictability directly to fluctuations in consumption.[8]

B. Predicting Stock Returns in Good and Bad Times

Some popular predictor variables are able to forecast returns in bad times as defined by recessions but not in good times, that is, during business cycle expansions (Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018)). In light of this, Cujean and Hasler (2017) develop a theoretical mechanism with heterogeneous agents that causes recession-centric stock return predictability. Several other studies emphasize the usefulness of financial institutions and intermediation together with frictions and market segmentation since the 2007 to 2009 subprime financial crisis for rationalizing stock market behavior and capturing the propagation of a shock in bad times as opposed to normal and good times (see the discussion in Cochrane (2017)).

The finding that returns are predictable only in bad times is a general concern for stan-

[8] As noted in Section I, the benchmark results reported in the paper are based on a cyclical consumption measure computed from equation (2) for $k = 24$. Table IAIV in the Internet Appendix shows that the forecasting power of cyclical consumption is significant across consumption horizons k ranging from one to 11 years ($k = 4, 8, ..., 44$). For any return holding period between one quarter and five years, the predictability is strongest at cycle lengths of five to six years (k between 20 and 24).

dard asset pricing models that emphasize the impact of time-variation in risk premia as a common explanation for asset prices. To examine whether the relation between future returns and cyclical consumption is present only in bad economic times, we estimate a linear two-state predictive regression model in the spirit of Boyd, Hu, and Jagannathan (2005):

$$r_{t,t+h} = \alpha + \beta_{bad} I_{bad} cc_t + \beta_{good} (1 - I_{bad}) cc_t + \varepsilon_{t,t+h}, \tag{4}$$

where $r_{t,t+h}$ is the h-quarter-ahead log excess return on the CRSP value-weighted index, I_{bad} is a state indicator that equals one during bad economic states and zero otherwise, and cc_t is one-quarter-lagged cyclical consumption. The parameters β_{bad} and β_{good} are the slope coefficients that capture the degree of return predictability in bad states and good states, respectively.

To evaluate the regression in equation (4), we first follow Dangl and Halling (2012) and Henkel, Martin, and Nardari (2011) and use the NBER-dated recessions to proxy for bad states, that is, the indicator variable I_{bad} takes a value of one during NBER-dated recessions and zero otherwise. Panel A of Table III presents the results.

[Table III about here]

An important finding is that the predictive power of cyclical consumption is not limited to bad times alone. In particular, the results in Panel A of Table III indicate that cyclical consumption provides a consistent description of future stock returns in both good and bad economic states. At the one-quarter horizon, the coefficient estimates are -0.83 (t-statistic of -1.86) in bad times and -0.37 (t-statistic of -2.61) in good times, with bootstrap p-values indicating statistical significance at the 5% and 1% level, respectively. To understand these results, note that a one-standard-deviation decrease in cc_t in bad times leads to an increase in expected excess returns of approximately three percentage points at a quarterly horizon, or roughly 12 percentage points at an annual horizon. The corresponding change in annualized returns during good times is slightly more than five percentage points. These estimates imply a total average reaction of future expected returns of close to 6.5 percentage points per annum. Differences in the level of statistical significance over bad and good times may be due to the fact that recessions are more infrequent than expansions (41 versus 243 data points in our 70-year sample). These results are notable because they stand in marked contrast to several studies that document predictability during economic recessions but no such predictability during economic expansions. Cyclical consumption typically retains its significance at the various horizons we consider. The $\bar{R}^2$ statistics in Panel A of Table III increase monotonically from 3.22% at a quarterly horizon to 35.01% at a horizon of five years.

To guard against the possibility that the results above are due to the specific dates used to define recessions, namely, those identified by NBER's Business Cycle Dating Committee, we next employ three alternative identifications of bad states. In Panel B of Table III we follow Rapach, Strauss, and Zhou (2010) and identify bad states using the bottom third of sorted real GDP growth. We download the series of real seasonally adjusted GDP from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis. In Panel C of Table III we define bad states as those periods in which the manufacturing purchasing managers index (PMI) issued by the Institute of Supply Management is below the optimal threshold value of 44.48 (Berge and Jordà (2011)). Finally, in Panel D of Table III, we define bad states as those periods in which cyclical consumption is one standard deviation below its mean. Over our full sample period, these four regime classifications identify 41, 94, 31, and 49 realizations as bad states, respectively.[9]

[9] To examine the robustness of the results, we experimented with a number of alternative definitions of bad states. First, we define bad states as periods with cyclical consumption 0.5, 1.5, or 2 standard deviations below its mean or as periods with the lowest 5%, 10%, 15%, 20%, or 25% of cyclical consumption realizations. Next, we defined bad regimes based on sorted values of real profit growth or real net cash flow growth as in Rapach, Strauss, and Zhou (2010). We also considered a measure of bad times from the Survey of Professional Forecasters (SPF) following Henkel, Martin, and Nardari (2011), and another one based on an unemployment recession gap of Stock and Watson (2010). The results indicate that cyclical consumption

Using these three alternative proxies for bad times, each of which is based on existing literature, we continue to find evidence of predictability in both bad and good times. In particular, the estimates of β_{bad} typically exceed the corresponding estimates of β_{good} (in absolute terms), but stock return predictability is not limited to relatively short recession periods alone. This result stands in sharp contrast to the predictability pattern reported in, for example, Henkel, Martin, and Nardari (2011) and Dangl and Halling (2012), who find that return predictability is driven predominantly by rare recession periods.

Taken together, the results in Table III provide consistent evidence that cyclical consumption has strong predictive ability both over time and across states of nature. This finding is novel, as the forecasting power of many predictor variables used in previous literature concentrates in relatively short time spans around adverse macroeconomic changes.

C. Alternative Detrending Methods

Since there is no a priori theoretical guidance regarding an appropriate choice of econometric procedure to isolate cyclical variation in consumption, it is useful to compare the predictive ability of cc with that of other empirical measures of cyclical consumption. We consider five such alternatives. First, following a voluminous literature in macroeconomics and finance, we assume a secular linear upward trend in consumption,

$$c_t = d_0 + d_1 t + \omega_t, \tag{5}$$

where the residual measures cyclical consumption, cc. Second we extend a linear trend formulation to allow for a breakpoint. This design allows one to account for the well-known decline in the macroeconomic risk, or in the volatility of the aggregate economy, in the

generally emerges as a strong predictor of stock returns in both good and bad times.

beginning of the 1990s.[10] Specifically, we estimate

$$c_t = \begin{cases} d_0 + d_1 t + \omega_t & \text{for } t \leq t_1 \\ d_0 + d_1 t + d_2 (t - t_1) + \omega_t & \text{for } t > t_1, \end{cases} \tag{6}$$

where the breakpoint t_1 corresponds to the first quarter of 1992 (see also Lettau, Ludvigson, and Wachter (2008)). In effect, equation (6) represents a piecewise OLS regression that fits two separate lines to disconnected data around the breakpoint.

We also consider higher-order time polynomials. In particular, we conveniently account for trends that change slowly over time by estimating a quadratic time trend model,

$$c_t = d_0 + d_1 t + d_2 t^2 + \omega_t, \tag{7}$$

as well as a cubic representation,

$$c_t = d_0 + d_1 t + d_2 t^2 + d_3 t^3 + \omega_t. \tag{8}$$

Finally, we follow Campbell (1991) and Hodrick (1992) and calculate a "stochastically detrended" consumption series as a backward-looking moving average based on a five-year window, where cyclical consumption in quarter t is equal to the difference between the natural logarithm of consumption in quarter t and the average of the natural logarithm of consumption in quarters t-20 to t-1. The six measures of cyclical consumption that we employ display cross-correlations in the range of 0.34 to 0.91.

[Table IV about here]

Table IV reports estimation results for equation (3) based on the alternative measures of cyclical consumption. We find that the predictive power of cyclical consumption holds

[10] An extensive macroeconomic literature finds evidence of a regime shift to lower-volatility real macroeconomic activity in the last two decades of the 20th century (see, for example, McConnell and Perez-Quiros (2000) and Stock and Watson (2002)).

regardless of how we detrend consumption. However, simple linear and quadratic trend specifications exhibit weaker long-run predictability, while the breaking and cubic detrending methods often yield stronger predictability than our benchmark results in Table I.

In sum, these results in Table IV suggest that using the detrending procedure of Hamilton (2018) as a benchmark specification provides a conservative view of return predictability. The results further suggest that the choice of method to employ in isolating cyclical variation in consumption appears to be largely irrelevant, as all of the methods that we consider reveal substantial return predictability.

D. Temporal Stability of Estimates

Welch and Goyal (2008) show that many business cycle predictor variables have performed poorly since the oil price crisis in the mid-1970s. To shed light on this observation, in Table V we examine predictability over three subsamples: 1980 to 2017, 1990 to 2017, and 2000 to 2017. The results for the first two subsamples are comparable to the full-sample results in Table I. In the post-2000 sample period, we find systematically larger coefficient estimates (in absolute terms) and $\bar{R}^2$s that are well beyond those reported in Table I. For example, focusing on the S&P500 index at the one-quarter and 20-quarter horizons, the estimates of β are -0.54 and -6.31 (t-statistics of -2.94 and -6.95) with $\bar{R}^2$s of 7.35% and 55.64% in the 2000-2017 sample, whereas the analogous estimates are -0.43 and -5.33 (t-statistics of -3.28 and -4.28) with $\bar{R}^2$s of 3.69% and 34.99% in the full sample.

[Table V about here]

We obtain similar results for three other periods: in the post-1965 data (see also Welch and Goyal (2008)), in a period pre-dating the global financial crisis, and in a sample that omits data in the aftermath of the run-up in prices in the early 2000s. We conclude that the predictive power of cyclical consumption fluctuations is not limited to any particular period and does not concentrate in subsamples associated with severe crises, a pattern often found in previous literature. This result is interesting given that many traditional predictor variables tend to display a reduction in the extent of predictability in the data after the mid 1970s.

We also examine the temporal stability of the β estimate from equation (3) to structural breaks as prescribed by Elliott and Müller (2006). Their proposed test statistic for the hypothesis that $\beta_t = \beta$ for all t and any h ($\widehat{qLL}$) is particularly useful in the context of predictive regressions because it is asymptotically efficient for a wide range of data-generating processes, has superior size properties in small samples compared to other popular statistics, and is simple to construct. Moreover, the simulation analysis in Paye and Timmermann (2006) shows that the test statistic of Elliott and Müller (2006) possesses excellent finite-sample size properties even in the presence of highly persistent lagged endogenous predictors. In Table IAV in the Internet Appendix, we show that the $\widehat{qLL}$ statistics for our benchmark estimates in Table I are not significant at any horizon (we find similar results for subsamples). These results emphasize the stability of the relation between consumption fluctuations and future expected stock returns.

E. Out-Of-Sample Analysis

Bossaerts and Hillion (1999) and Welch and Goyal (2008) point out that in-sample predictability of stock returns is not necessarily robust to out-of-sample validation and therefore in-sample predictability does not generally indicate that it is possible to obtain reliable out-of-sample forecasts. Out-of-sample results may differ from in-sample results due to loss of information when splitting samples in out-of-sample tests, structural breaks, and parameter uncertainty (see, for example, Inoue and Kilian (2004), Paye and Timmermann (2006), Lettau and Van Nieuwerburgh (2008), and Cochrane (2008)). Furthermore, Nagel and Xu (2018) show that in-sample predictability does not necessarily imply that out-of-sample predictability will hold in models with learning.

There are at least two possible interpretations of out-of-sample tests. On the one hand, one can use out-of-sample testing to validate in-sample relations. On the other hand, one can use out-of-sample testing to determine whether a sophisticated investor could construct a real-time trading strategy.[11] One may assume, for example, that the econometrician has limited information relative to the economic agent. Under this view, in contrast to the econometrician, economic agents know the history of prior consumption and its relation to the consumption trend, and hence they know how stock returns react to real quantities. Alternatively, one may assume that economic agents wait until consumption is reported (often with a lag) and then calculate cyclical consumption based on real-time data to form a forecast of the next period's return in order to trade. The framework one chooses has implications for how to conduct the out-of-sample tests. Since our main objective is to examine the validity of the in-sample evidence on the stability of cyclical consumption to predict future returns, rather than to create a trading strategy, we follow the "economic agents know" framework. This allows us to use current, that is, revised or latest-available, consumption data and a one period lag in the predictability regression.

We proceed as follows. First, using the revised consumption data, we recursively estimate cyclical consumption each quarter using data available at the time of the forecast. Next, we employ these values of cyclical consumption in recursive predictive regressions for stock returns to form out-of-sample forecasts. We use an expanding estimation window where the coefficients in the return forecasting regression are estimated recursively using only the information available through time t in forecasting over the next h quarters. To ensure that our results are not sensitive to the choice of evaluation period, we perform out-of-sample tests for three different out-of-sample forecasting periods: 1980Q1 to 2017Q4, 1990Q1 to 2017Q4, and 2000Q1 to 2017Q4.[12]

[11] We thank an anonymous referee for highlighting the distinction between the two perspectives for interpretation of out-of-sample predictability tests.

[12] Starting the out-of-sample evaluation in 1980 provides a reasonably long initial in-sample period for reliably estimating the parameters used to generate the first predictive regression forecast. This issue is of particular relevance for us because consistent estimation of the trend parameters in cc requires a large number of observations.

For nested forecast comparison tests, we specify a model of constant expected returns, that is, a benchmark model in which a constant is the sole explanatory variable. The constant expected return model is a restricted nested version of an unrestricted model of time-varying expected returns, which includes both a constant and *cc*. To this end, we compare the forecasting error from a series of out-of-sample return forecasts obtained from a prediction equation that includes a constant and *cc* (the unrestricted model) to that from a prediction equation that includes a constant as the sole forecasting variable (the restricted model). For example, Welch and Goyal (2008) show that the historical average forecast is a very stringent out-of-sample benchmark.

E.1. Baseline Out-of-Sample Results

In Table VI, we report results of out-of-sample predictions of the log excess return on the CRSP value-weighted index over various horizons ranging from one quarter to five years. We find that the unrestricted model typically generates significantly better forecasts than the restricted model. For instance, the ENC-NEW test of Clark and McCracken (2001) rejects the null hypothesis that the forecasts from the constant expected return model encompass the forecasts from the time-varying expected return model at the 1% level for all horizons and all forecasting periods that we consider. The MSE-F test of McCracken (2007) rejects the null hypothesis that the mean squared errors from the unrestricted model are greater than or equal to those from the historical average return.

[Table VI about here]

The out-of-sample R^2_{OOS} statistics in Table VI are all positive, meaning that our cyclical consumption measure systematically delivers a lower average forecasting error than the historical average forecast. For example, at the one-quarter horizon, the R^2_{OOS} is 0.64% (significant at the 10% level) when we forecast from 1980, 1.96% (significant at the 10%

level) when we forecast from 1990, and 1.35% (albeit insignificant) when we forecast from 2000. When we compare these measures of fit with the corresponding R^2 statistics from the in-sample regressions in Table V – 1.86% for the post-1980 period, 2.96% for the post-1990 period, and 5.56% for the post-2000 period – we find, consistent with Bossaerts and Hillion (1999) and Welch and Goyal (2008), a lower out-of-sample fit for each forecast evaluation period that we consider at a horizon of one quarter.

At horizons greater than one quarter, the R^2_{OOS} statistics are all statistically significant. They are often close to, but remain systematically below, their in-sample counterparts in both the early 1980 to 2017 and the late 2000 to 2017 evaluation periods. In the post-1990 sample, the out-of-sample R^2 estimates are lower than the corresponding in-sample measures of fit for horizons of up to two years while the reverse is true for longer-term returns at horizons of between three and five years.

E.2. Additional Out-of-Sample Results

In a robustness test, we follow Lettau and Ludvigson (2001) and consider a scenario in which the predictive regression is estimated recursively each time a forecast is made but the parameters in cc are fixed at their values estimated over the full sample. This technique might be advantageous because it does not induce sampling error in the estimation of parameters in cc, especially in the early estimation recursions. Table IAVII in the Internet Appendix shows that using full-sample estimates to measure cc often leads to stronger out-of-sample predictive power (exceptions include the results for longer-horizon returns in the post-1980 sample). This result suggests that the reestimation of the parameters in cc induces sampling error in the parameter estimates, which may lead to less accurate forecasts.[13]

[13] We also investigate the out-of-sample predictive power of cyclical consumption using real-time data instead of revised data. The results reported in Table IAVIII in the Internet Appendix are largely consistent with our benchmark findings in Table VI.

To summarize, our results show that cyclical fluctuations in consumption display statistically significant out-of-sample predictive power for aggregate stock market returns, regardless of whether the out-of-sample forecasting starts in 1980, 1990, or 2000. These results are in contrast to Welch and Goyal (2008), who conclude that a long list of popular business cycle predictor variables have been unsuccessful out-of-sample over the last few decades, an issue we return to in Section IV.

III. Further Robustness Tests and Extensions

In this section, we first investigate the predictive ability of cyclical consumption for stock returns sorted into industry portfolios. We next explore the robustness of our results to alternative ways of defining consumption. Finally, we examine international evidence.

A. Industry Portfolios

In the analysis above, we assess the predictability of stock returns based on two commonly used stock market indices that give a broad view of the behavior of the aggregate equity premium. In this section, we investigate the extent to which cyclical consumption can forecast returns on portfolios of stocks sorted on industry SIC codes.[14]

[Table VII about here]

Table VII reports estimation results from univariate predictive regressions for each of the 10 industry portfolios. In line with our results for the total market portfolios in Table I, we find that cyclical consumption emerges as a powerful predictor of the cross section of industry returns. In particular, the inverse relation between cyclical consumption and future expected returns is visible for all of the industry portfolios, with significant results (usually at the 1% significance level) across all industries except the energy category. We further find that the regression slopes and $\bar{R}^2$ statistics vary across industries, illustrating cross-sectional

[14] The portfolio data come from Ken French's online data library.

differences in the sensitivities. In particular, returns on durable goods and hi-tech business equipment have the highest level of predictability. Overall, the results in Table VII reinforce our conclusion that fluctuations in cyclical consumption predict stock returns and emphasize that time-varying expected rates of return contain a common macroeconomic component.

B. Alternative Consumption Measures

In our main empirical analysis we focus on real per capita NIPA expenditures on non-durable goods and services as a proxy for aggregate consumption. In this section we consider the predictive ability of cyclical consumption extracted from various subcategories of personal consumption expenditures (PCE), including i) nondurable goods (NON), ii) services (SERV), iii) durable goods (DUR), iv) the stock of durable goods (SDUR) constructed from the year-end estimates of the chained quantity index for the net stock of consumer durable goods published by the BEA following Yogo (2006), v) nondurable and durable goods (GOODS), and vi) total PCE.

[Table VIII about here]

Table VIII reports results from the benchmark regression (3) applied to the log excess return on the value-weighted CRSP index. The predictive power of cyclical consumption is generally qualitatively similar in terms of coefficient magnitude, statistical significance, and $\bar{R}^2$ across the six different expenditure aggregates that we consider. According to the $\bar{R}^2$ statistics, nondurable goods is the strongest predictor of stock returns, with $\bar{R}^2$ values of 3.18% and 45.42% for quarterly and five-year returns, respectively. However, the extent of predictability is similar across consumption categories except those that involve durables, for which the extent of predictability is weaker, particularly at the one-quarter-horizon. It is interesting to note that the predictive ability of the aggregate consumption proxy in Table I is comparable to that of nondurables and services measured separately. We also note that at horizons of three years and above, we often find stronger results based on alternative

PCE categories in Table VIII than in Table I. This evidence reinforces our main findings and further highlights the conservative nature of our benchmark results.

C. International Evidence

To mitigate concerns with respect to overfitting or "data snooping" (Lo and MacKinley (1990) and Bossaerts and Hillion (1999)), we investigate the predictability of stock returns in international equity markets. We follow Ang and Bekaert (2007), Hjalmarsson (2010), and Rapach, Strauss, and Zhou (2013) and obtain international total return indices in national currency from Morgan Stanley Capital International (MSCI), which has recorded this information since the beginning of 1970. We consider seven major developed market indices namely, the MSCI World, the MSCI World ex USA, the MSCI EAFE, the MSCI Europe, the MSCI Pacific, the MSCI Far East, and the MSCI G7 indices.[15] We focus attention on actual returns because appropriate proxies for regional risk-free rates and inflation rates are not available. We obtain similar results for returns denominated in U.S. dollars, for excess returns computed by subtracting the U.S. Treasury bill rate as a proxy for the world risk-free rate, and for real returns computed by subtracting the U.S. CPI inflation rate as a proxy for the global inflation rate.

In what follows, we examine whether a global measure of variation in cyclical consumption has significant predictive power for future stock returns around the world. This approach is motivated by the fact that world-wide rather than local fluctuations in the business cycle

[15] The MSCI World equity index consists of 23 developed market countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The World index covers approximately 85% of the free float-adjusted market capitalization in each country. The MSCI EAFE index represents 21 developed market countries, namely, the MSCI world countries less the United States and Canada. The MSCI Europe consists of 15 major developed European countries. The MSCI Pacific index consists of five developed market countries – Australia, Hong Kong, Japan, New Zealand, and Singapore – while the MSCI Far East index includes Hong Kong, Japan, and Singapore.

have gained importance over recent decades (Lumsdaine and Prasad (2003) and Kose, Otrok, and Whiteman (2003)). To the extent that a global cyclical consumption component can capture common business cycle related risks, our analysis contributes to the debate about the level of integration in financial markets (Pukthuanthong and Roll (2009), and Rangvid, Santa-Clara, and Schmeling (2016)).

To this end, we compute global cyclical consumption as the simple arithmetic average of country-specific measures of cyclical consumption. The latter are obtained by fitting the regression in equation (1) to the logarithm of real seasonally adjusted consumption expenditures in the 20 developed market countries from the MSCI World index for which consumption data are available from the OECD database over the full sample period (i.e., not including Hong Kong, Israel, and Singapore).[16]

[Table IX about here]

The results on international predictability are reported in Table IX. We find a stable negative relation between cyclical consumption and future stock returns. This relation is always economically and statistically significant. In terms of economic magnitudes, the international estimates imply an even stronger impact of cyclical consumption on expected returns than our benchmark findings for the U.S. For instance, we find that a one-standard-deviation decrease in global cyclical consumption would lead to an increase in the expected return on the MSCI World index on the order of about 7.5 percentage points per annum. The corresponding Newey and West (1987) t-statistic of -3.59 and the bootstrap p-value indicate significance at the 1% level. Variation in cyclical consumption accounts for 5.32% of the variation in the quarterly world market return. Cyclical consumption retains its predictive power at any return horizon that we consider, with associated $\bar{R}^2$ statistics climbing to 46.75%, 53.97%, and 51.86% for $h = 12$, 16, and 20 quarters, respectively.

[16] We considered a number of alternative global measures of cyclical consumption such as a GDP-weighted average or the first principal component of the national cyclical consumption series. We also experimented with consumption data for the G7 countries only. Our conclusions were generally unaffected.

The results are broadly similar across the different regions with predictability, perhaps not surprisingly due to the more recent sample period, being strongest for the G7 region while weakest for the Pacific region. The consistency of the estimated sign, its size, and its statistical significance supports the view that cyclical consumption is useful in tracking future movements in global equity returns. These results are in line with our benchmark findings and suggest that our main results are not specific to the U.S. stock market.

IV. Alternative Predictor Variables

How does the predictive information contained in cyclical consumption compare to other well-known predictor variables that have been rationalized by their ability to track business cycle conditions? To address this question, we conduct a set of out-of-sample tests using alternative business cycle variables that come from the extant literature. In particular, the forecasting variables that we consider include the 15 predictors studied by Welch and Goyal (2008),[17] the share of labor income to consumption (s^w) of Santos and Veronesi (2006), the consumption-wealth ratio (cay) of Lettau and Ludvigson (2001), the consumption volatility measure (σ_c) of Bansal, Khatchatrian, and Yaron (2005), and the output gap (gap) of Cooper and Priestley (2009).

We use revised macroeconomic data to compute s^w, cay, σ_c, gap, and cc. To compute the share of labor income to consumption, we follow Santos and Veronesi (2006) and use the definition of labor income in Lettau and Ludvigson (2001). The data for total personal consumption expenditures, labor income, and asset wealth, which are used to compute the consumption-wealth ratio, are downloaded from the website of Martin Lettau. We calculate consumption volatility as $\sigma_{c,t-1,J} \equiv \log\left(\sum_{j=1}^{J} \left|\eta_{c,t-j}\right|\right)$, where $\eta_{c,t}$ is the residual from an AR(1) process of the log growth rate of real per capita nondurables and services and $J = 4$ quarters following Bansal, Khatchatrian, and Yaron (2005). The output gap is constructed

[17] We obtain these data from the online library of Amit Goyal.

from industrial production data available at the Federal Reserve Bank of St. Louis following Cooper and Priestley (2009).

In sum, we employ a total of 19 alternative predictor variables:

1. Log dividend-price ratio (dp): the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of prices on the S&P 500 index.

2. Log dividend yield (dy): the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of lagged prices on the S&P 500 index.

3. Log earnings-price ratio (e/p): the log of a 12-month moving sum of earnings on the S&P 500 index minus the log of prices on the S&P 500 index.

4. Log dividend-payout ratio (d/e): the log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings on the S&P 500 index.

5. Stock variance ($svar$): the sum of squared daily returns on the S&P 500 index.

6. Book-to-market ratio (b/m): the ratio of book value to market value for the Dow Jones Industrial Average.

7. Net equity expansion ($ntis$): the ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.

8. Treasury bill rate (tbl): the interest rate on a three-month Treasury bill (secondary market).

9. Long-term yield (lty): the long-term government bond yield.

10. Long-term return (ltr): the return on long-term government bonds.

11. Term spread (tms): the long-term yield on government bonds minus the Treasury bill rate.

12. Default yield spread (dfy): the difference between the BAA- and AAA-rated corporate bond yields.

13. Default return spread (dfr): the long-term corporate bond return minus the long-term government bond return.

14. Inflation (*infl*): the growth in the Consumer Price Index (CPI) for all urban con-

sumers.

15. Investment-to-capital ratio (i/k): the log ratio of aggregate private nonresidential fixed investment to aggregate capital for the whole economy (Cochrane (1991)).

16. Share of labor income to consumption (s^w): the ratio of employee compensation to the consumption of nondurables plus services (Santos and Veronesi (2006)).

17. Consumption-wealth ratio (cay): the residual from a cointegrating relation between log consumption, log asset (nonhuman) wealth, and log labor income (Lettau and Ludvigson (2001)).

18. Consumption volatility (σ_c): the log of a backward-looking moving average of the absolute innovations in consumption growth based on a four-quarter window (Bansal, Khatchatrian, and Yaron (2005)).

19. Output gap (gap): the residual from a regression of log of industrial production on a time trend that contains linear and quadratic components (Cooper and Priestley (2009)).

We employ a recursive out-of-sample methodology as in Section II.E to calculate equity premium forecasts for each predictor. We use the 1953Q4 to 1979Q4 sample as the initial estimation period and expand it by one quarter in each recursion. Forecasting ability is evaluated by means of the out-of-sample R^2 statistic (R^2_{OOS}).[18]

[Table X about here]

Table X presents results of out-of-sample horse races that pit the forecasts for each predictor variable against the historical average return benchmark forecast. The overall picture is that the traditional predictive variables have weak out-of-sample predictive power. At a

[18] Table IAI in the Internet Appendix provides descriptive statistics for the predictor varaibles. Table IAII shows that the in-sample predictive power of cc compares favorably with that of standard business cycle predictor variables. Of the 19 alternative economic predictors that we consider, only four variables – the term spread (tms), the investment-to-capital ratio (i/k) of Cochrane (1991), the consumption-wealth ratio (cay) of Lettau and Ludvigson (2001), and the output gap (gap) of Cooper and Priestley (2009) – exhibit significant and strong predictive ability for stock returns. The remaining variables are typically insignificant at the 5% level and/or generate low R^2s.

horizon of one quarter, 18 out of 19 alternative predictors generate a negative R^2_{OOS} and thus fail to outperform the historical average forecast. This result echoes the message of Welch and Goyal (2008) that many economic variables deliver highly erratic out-of-sample performance in the period after the oil price shocks of the 1970s. In marked contrast to this observation, the predictive power of cc stands out. The quarterly R^2_{OOS} statistic for cc is positive at 0.64% (significant at the 10% level), which means that unlike many popular predictors, cc outperforms the prevailing mean benchmark and clears the out-of-sample hurdle.

A similar picture holds at longer horizons. For example, at horizons of one, two, and three years, we register negative R^2_{OOS} statistics for 17 out of 19 alternative predictor variables (the two exceptions with positive R^2_{OOS} statistics are tms and i/k), whereas cc generates positive R^2_{OOS} statistics of 4.14%, 10.55%, and 17.63% (significant at the 1% level), respectively. Overall, for return holding periods of up to three years, cc emerges as the most powerful predictor in our sample. At horizons of four and five years, i/k is the only variable that yields R^2_{OOS} statistics that slightly exceed those produced by cc.

To summarize, the results in Table X confirm the strong and stable predictive ability of cyclical consumption relative to numerous popular business cycle predictors. In particular, we find that none of the 19 traditional predictor variables usually considered in the literature can systematically generate better out-of-sample forecasts of the equity premium than cyclical consumption. Welch and Goyal (2008) demonstrate that it is difficult to identify individual economic variables capable of generating reliable out-of-sample forecasts. Against this backdrop, we show that cyclical consumption outperforms the historical average by meaningful margins and generates better forecasts than popular forecasting variables.

V. The External Habit Model

The regression analysis in Section II documents an inverse relation between cyclical consumption and future expected stock returns: a decrease (increase) in consumption below (above) trend indicates bad (good) times when marginal utility of current consumption and future expected returns are high (low). A natural question is how this empirical evidence relates to consumption-based asset pricing theory, which aims to explain the dynamic behavior of asset returns using aggregate consumption data.[19]

Campbell and Cochrane (1999), for example, assume that investors evaluate current consumption relative to a habit level of consumption that can be thought of as a weighted moving average of past consumption expenditures.[20] In their model, habit acts as a trend for consumption: a decline in consumption relative to the trend during a recession leads to high expected returns and low asset prices. One may thus wonder how our detrended consumption variable relates to consumption habit, and what restrictions such a relation may impose on the consistency of our choice of the cycle parameter k in the Hamilton (2018) filter with respect to return predictability. To address these questions, we examine the implications of the habit model of Campbell and Cochrane (1999) for time-varying expected returns. Specifically, in Section V.A, we develop a simple economic framework wherein cyclical consumption emerges as a relevant predictor variable for future stock returns. In Section V.B we discuss calibration details and in Section V.C we examine the compatibility of our results with the predictability generated by the model.

[19]Countercyclical variation in risk premia has been incorporated in prominent equilibrium models that can generate time-varying expected returns, including models with time-varying risk aversion (Campbell and Cochrane (1999)), time-varying aggregate consumption risk (Bansal and Yaron (2004)), and time-varying disaster risk (Farhi and Gabaix (2016) and Wachter (2013)).

[20]The empirical analysis in Bansal, Kiku, and Yaron (2012) and Beeler and Campbell (2012) points to an important distinction between the habit model of Campbell and Cochrane (1999) and the long-run risks model of Bansal and Yaron (2004). Specifically, the long-run risks model implies that past or current consumption cannot explain future dividend-price ratios or returns, while the habit model suggests that asset prices are backward-looking and that past consumption growth forecasts future price-dividend ratios and returns.

A. Consumption Habit, Cyclical Consumption, and Time-Varying Returns

Campbell and Cochrane (1999) augment the standard power utility function with a time-varying subsistence level X_t that represents the agent's "external habit" and is defined indirectly through the surplus consumption ratio $S_t \equiv \frac{C_t - X_t}{C_t}$. To ensure stationarity and prevent habit from falling below consumption, Campbell and Cochrane (1999) assume that the log surplus consumption ratio, $s_t \equiv \log(S_t)$, follows a mean-reverting heteroskedastic first-order autoregressive process,

$$s_{t+1} = (1-\phi)\,\overline{s} + \phi s_t + \lambda(s_t)\,\upsilon_{t+1}, \tag{9}$$

where $\overline{s}$ is the steady-state value of s_t, ϕ is the habit persistence parameter, and $\lambda(s_t)$ is a nonlinear monotonically decreasing sensitivity function that determines how innovations in consumption growth υ_{t+1} influence s_{t+1}. Surplus consumption, the only state variable in the model, controls the price of risk and generates time-variation in expected returns.

Appendix C in the working paper of Wachter (2006) formally demonstrates that a first-order approximation around $s_t = \overline{s}$ implies that surplus consumption gradually adjusts to the history of current and past consumption with coefficient ϕ,

$$s_t \approx \kappa + \lambda(\overline{s}) \sum_{j=0}^{\infty} \phi^j \Delta c_{t-j}, \tag{10}$$

where κ is a constant depending on model parameters. The model requires a high, but less than unity, value of ϕ to match stock market data. While in theory surplus consumption is influenced by past consumption going back to infinity, a "cut-off" horizon can be used to obtain an empirical proxy for s_t. If we omit the constant κ and the proportionality parameter $\lambda(\overline{s})$, and if we assume a close to unity value of the persistence parameter ($\phi \approx 1$), it follows that there exists a close link between a finite-horizon proxy for surplus consumption and cyclical consumption,

$$\hat{s}_t \approx c_t - c_{t-k} \approx cc_t, \tag{11}$$

where k determines the length of time over which habit reacts to past consumption. The second approximation in (11) follows from the fact that under the random walk hypothesis for consumption, Hamilton's (2018) detrending procedure reduces to a difference filter. This is because, for large samples, the OLS estimates in equation (1) converge to $b_1 = 1$ and all other $b_j = 0$. The resulting cyclical component is then given simply as the difference over a k-quarter horizon, or equivalently, as the sum of the observed changes over k periods.

If excess returns on the stock market and consumption growth are jointly conditionally lognormally distributed, the Campbell and Cochrane (1999) model implies that

$$E_t\left(r_{t+1}\right) + \frac{1}{2}\sigma_t^2 = \gamma_t cov_t\left(r_{t+1}, \Delta c_{t+1}\right), \tag{12}$$

where $E_t\left(r_{t+1}\right)$ is the expected log excess stock return, γ_t is the state-dependent price of consumption risk defined as $\gamma_t = \gamma\left(1 + \lambda\left(s_t\right)\right)$, $cov_t\left(r_{t+1}, \Delta c_{t+1}\right)$ is the amount of risk, and $\frac{1}{2}\sigma_t^2$ is a Jensen's inequality term. Since $\lambda\left(s_t\right)$ is inversely related to s_t, and cc_t and s_t are tightly linked as they both depend on past consumption growth, it follows that low levels of cyclical consumption increase γ_t and forecast high expected returns. This prediction turns out to be consistent with the empirical evidence that we present in Section II. The inverse relation between s_t, and therefore cc_t, and risk premia also operates via the conditional covariance term in equation (12), because a decrease in consumption toward the habit level in bad times is associated with an increase in $cov_t\left(r_{t+1}, \Delta c_{t+1}\right)$ in the model. Overall, the dependence of expected returns on surplus consumption is close to linear as illustrated in Figure 4 in Campbell and Cochrane (1999), except for very low values of the surplus consumption ratio.[21]

[21]Note also that the effect of the Jensen's inequality term is quite small empirically. For instance, we obtain a coefficient of -0.41 (t-statistic of -3.07) and an $\bar{R}^2$ of 3.11% in the benchmark predictive regression for quarterly excess CRSP returns in equation (3) compared to an estimate of -0.42 (t-statistic of -3.06) and

B. Parameter Calibration

We proceed by conducting a simple simulation study with two purposes. First, we would like to evaluate the extent to which the habit model of Campbell and Cochrane (1999) can match the time-series predictability of stock returns in the data. Second, we would like to analyze the frequency at which consumption innovations are related to expected returns. We employ Campbell and Cochrane's (1999) parameter values to simulate a sample path of 1,000,000 quarters of artificial data for returns on stocks and consumption growth from the model.[22] We then calculate population values for a variety of statistics. Table XI compares simulated means and standard deviations implied by the model to corresponding statistics in our empirical sample over the 1947Q1 to 2017Q4 period. Following Campbell and Cochrane (1999), we set average log consumption growth to 1.89% and its standard deviation to 1.50%, which should be measured against the values of 1.89% and 1.00% in our empirical sample (all terms per annum). As for the remaining parameter choices, the utility curvature parameter is set to $\gamma = 2.00$, the persistence parameter of the log surplus consumption ratio to $\phi = 0.87$, and the subjective discount factor to $\delta = 0.89$. As Table XI shows, we can closely match the means and standard deviations of consumption growth and excess returns as well as their Sharpe ratios using either the consumption claim or the dividend claim to model the market return.[23]

[Table XI about here]

an $\bar{R}^2$ of 3.16% for log excess CRSP returns in Table I.

[22]Campbell and Cochrane (1999) pick parameters by calibrating the model to match certain moments in the post-war U.S. data over the 1947 to 1995 period. Our 1947 to 2017 sample yields similar statistics as in Table 2 in Campbell and Cochrane (1999). For instance, in the two samples, the mean of the log consumption growth is 1.89 and 1.89, the standard deviation of log consumption growth is 1.50 and 1.00, the Sharpe ratio for log stock returns is 0.43 and 0.40, the Sharpe ratio for simple returns is 0.50 and 0.49, the average of the log excess stock returns is 6.64 and 6.52, and the standard deviation of log stock returns is 15.20 and 16.38 in percent per annum.

[23]See the Internet Appendix for further simulation details.

C. Implications for Stock Return Predictability

In this section we use our simulations to investigate the model's ability to reproduce the results in Section II, that is, the inverse relation between cyclical consumption and future expected stock returns. In addition, the simulations allow us to assess the impact of cycle length on asset prices and study the frequency at which consumption innovations are incorporated into risk prices.

[Table XII about here]

To begin, we analyze the population properties of the model for in-sample predictability of stock returns. Based on a sample path of 1,000,000 quarterly simulations, we compute a long series of artificial realizations of log excess returns and our cyclical consumption variable as defined in (11) for $k = 24$.[24] We then examine the extent of model-implied predictability by estimating the standard predictive regression (3). The upper row of Table XII, Panel A reports the estimates in simulated data implied by the consumption claim, the middle row presents simulation results for the dividend claim, and the entries in the bottom row replicate the findings in the historical data (see also Table I). We report OLS estimates of the slope coefficients and adjusted $\bar{R}^2$ statistics in percent. We do not report t-statistics of the simulation results because the large sample size makes them meaningless.

As one can see, cyclical consumption can predict returns at various horizons ranging from one quarter to five years. The slope coefficients have the same (negative) sign in the model as in the empirical regressions. The model's predictions for the consumption claim are somewhat weaker compared to the actual data but the general patterns are similar. In the model, when using the consumption claim, the slope coefficients increase (in absolute terms) from -0.22 at a horizon of one quarter to -3.04 at a horizon of five years, while in the

[24] We also examined predictability in the historical data for a measure of cyclical consumption computed from a difference filter in (11) and obtained results that are similar to our benchmark findings.

actual data they increase (in absolute terms) from -0.42 to -5.01.[25] For the dividend claim, the predictive coefficients on cyclical consumption are similar to those on the consumption claim, but the adjusted $\bar{R}^2$ statistics are lower. For instance, for the consumption claim the population $\bar{R}^2$s increase from 1.75% at the one-quarter horizon to 23.80% at the five-year horizon, whereas the measures of regression fit using the dividend claim are 1.46% and 18.13% (see also Campbell and Cochrane (1999)). For comparison, the corresponding $\bar{R}^2$s in the actual post-war sample are around 3% for quarterly returns and close to 35% for five-year returns.

We next assess out-of-sample predictability in the model by generating 2,500 artificial samples of size 284, which matches the number of observations in our post-war historical sample. For each artificial sample, we then compute 112-(h-1) out-of-sample forecasts, which matches the number of forecasts in the 1990 to 2017 evaluation window. The upper row of Table XII, Panel B reports average out-of-sample R^2 values across the 2,500 artificial samples for the consumption claim, the middle row reports corresponding statistics for the dividend claim, and the bottom row replicates the results in the historical data (see also Table VI). For the consumption claim, we find that cyclical consumption consistently outperforms the historical mean in forecasting returns out-of-sample for each forecast horizon h, with out-of-sample R^2 measures increasing from 1.00% for quarterly returns to 9.51% for five-year returns. The out-of-sample R^2 values with the dividend claim are generally lower across all horizons but still positive. Overall, as expected, we see more predictability in the historical sample compared to the model out-of-sample.

Finally, Table IAX in the Internet Appendix presents results on the impact of cycle length on the model fit. For consistency with Table IAIV, we study a total of 11 specifications with consumption cycles k varying from four to 44 quarters. Similar to the patterns in the

[25] Table IAIX in the Internet Appendix shows that cyclical consumption displays a comparable degree of volatility and autocorrelation in actual and simulated data. For example, the standard deviation and first-order autocorrelation are 3.74% and 0.97 in actual data compared to 3.66% and 0.96 in simulated data.

historical sample, the simulations indicate that the predictive power of cc is increasing in k up to cycle lengths of around five or six years, almost stagnating for values of k between six and eight years, and slightly deteriorating thereafter. The predictive coefficients on cyclical consumption are similar for both claims, but the $\bar{R}^2$ statistics tend to be lower when using the dividend claim compared to the consumption claim. The findings generally indicate that returns adjust to changing economic conditions at frequencies of around five to six years, giving a macroeconomic, consumption-related foundation for the existence of risk determinants in asset prices that are due to low-frequency dynamics. This insight supports our choice of a six-year cycle in the benchmark application of Hamilton's (2018) filter in Section II.[26]

In summary, we find that simulated data from the Campbell and Cochrane (1999) model produce an inverse relation between cyclical consumption and future expected stock returns consistent with what we find in the empirical data. In particular, the model generates qualitatively similar patterns but yields lower predictability, especially for longer horizon returns. In addition, we find that values of around five to six years are optimal for the parameter k in the Hamilton (2018) filter in terms of capturing predictable variation in expected returns.

VI. Conclusion

The predictability of stock returns has been rationalized as evidence of time-variation in expected risk premia. Common predictor variables, however, have been largely unsuccessful in establishing a sound relation with fundamentals (Cochrane (2005), Welch and Goyal (2008), and Henkel, Martin, and Nardari (2011)).

[26] While cc captures a slow-moving business cycle related risk premium component, cay is less persistent and works particularly well at business cycle frequencies of relatively short horizons as shown by Lettau and Ludvigson (2001). In our sample, the half-life of cc is about five years, while that of cay is about two years, which illustrates that cc works at a lower frequency than cay.

In this paper, we propose a novel consumption-based predictive variable – cyclical consumption – and show that it captures a significant fraction of the variation in expected stock returns. To identify a cyclical component of consumption, which measures deviations of aggregate consumption from its trend, we employ the robust linear projection method of Hamilton (2018). We document a robust inverse relation between cyclical consumption and future expected returns: when economic conditions deteriorate, often referred to as bad times, consumption drops below its trend, which leads to an increase in the marginal utility of current consumption. As a consequence, prices fall and future expected returns rise. Conversely, in good times when consumption rises above trend and marginal utility from consumption is low, prices rise and future expected returns fall. The empirical evidence that we document links the consumption decisions of agents to time-variation in expected returns in a manner consistent with rational asset pricing and suggests that stock return predictability arises as a rational response to changing business conditions.

Our findings are consistent with theoretical explanations of asset prices that emphasize the role of habit formation in consumption, such as Campbell and Cochrane (1999). Using simulations, we show that the habit model produces a similar inverse relation between expected returns and cyclical consumption. Our analysis emphasizes that low-frequency fluctuations in consumption capture slow-moving countercyclical variation in expected returns.

We conduct a battery of additional tests and conclude that the predictive power of cyclical consumption is greater than that of many commonly used forecasting variables, is stable over time, is not confined to bad times or times of crisis, is evident in industry portfolio and international data, and is robust to a variety of alternative specifications and methods used to isolate cyclical variation in consumption. Taken together, our evidence lends support to asset pricing models based on external habit formation where the dynamics of expected returns are driven by changes in the level of current consumption relative to its prior history.

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Table I
Benchmark Predictive Regressions

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log stock market return, and cc_t is one-quarter-lagged cyclical consumption. The table shows results for log excess market returns (Panel A), log real market returns (Panel B), and log market returns (Panel C) for the S&P 500 index and the CRSP value-weighted index. For each regression, the table reports the slope estimate, Newey-West corrected t-statistics in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values. The sample covers the period from 1953Q4 to 2017Q4.

	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
			Panel A: Excess Market Returns			
SP500	-0.43	-1.60	-2.72	-3.36	-4.34	-5.33
	(-3.28)***	(-3.83)***	(-4.21)***	(-4.65)***	(-4.69)***	(-4.28)***
	[3.69]	[12.93]	[20.79]	[24.70]	[32.36]	[34.99]
CRSP	-0.42	-1.55	-2.57	-3.13	-4.08	-5.01
	(-3.06)***	(-3.59)***	(-3.96)***	(-4.47)***	(-4.57)***	(-4.17)***
	[3.16]	[11.43]	[18.68]	[22.46]	[31.53]	[34.46]
			Panel B: Real Market Returns			
SP500	-0.41	-1.56	-2.67	-3.33	-4.38	-5.54
	(-3.11)***	(-3.55)***	(-3.84)***	(-4.12)***	(-4.17)***	(-3.97)***
	[3.34]	[11.71]	[18.47]	[21.51]	[28.19]	[31.45]
CRSP	-0.40	-1.51	-2.52	-3.10	-4.12	-5.22
	(-2.91)***	(-3.34)***	(-3.62)***	(-3.95)***	(-3.99)***	(-3.80)***
	[2.87]	[10.45]	[16.83]	[19.93]	[28.04]	[31.66]
			Panel C: Market Returns			
SP500	-0.35	-1.28	-2.11	-2.51	-3.33	-4.26
	(-2.65)***	(-3.00)***	(-3.05)***	(-3.05)***	(-3.16)***	(-3.15)***
	[2.36]	[8.51]	[12.86]	[13.94]	[19.06]	[22.16]
CRSP	-0.34	-1.23	-1.96	-2.28	-3.07	-3.94
	(-2.47)**	(-2.80)***	(-2.84)***	(-2.87)***	(-3.02)***	(-3.05)***
	[1.98]	[7.38]	[11.18]	[12.06]	[17.87]	[21.11]

Table II
IVX-Wald Statistics

This table reports IVX-Wald statistics of Kostakis, Magdalinos, and Stamatogiannis (2015) for the OLS regressions summarized in Table I. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$h = 1$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Panel A: Excess Market Returns						
SP500	9.72***	9.38***	7.72***	6.38**	7.11***	7.83***
CRSP	8.43***	7.89***	6.19**	4.95**	5.63**	6.23**
Panel B: Real Market Returns						
SP500	8.54***	8.38***	7.00***	5.87**	6.80***	7.89***
CRSP	7.45***	7.09***	5.63**	4.57**	5.42**	6.35**
Panel C: Market Returns						
SP500	5.99**	5.60**	4.29**	3.25*	3.81**	4.51**
CRSP	5.15**	4.63**	3.61*	2.37	2.87*	3.45*

Table III
Predictability in Good and Bad Times

The table presents results of two-state predictive regressions of the form $r_{t,t+h} = \alpha + \beta_{bad} I_{bad} cc_t + \beta_{good} (1 - I_{bad}) cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log excess return on the CRSP value-weighted index, cc_t is one-quarter-lagged cyclical consumption, and I_{bad} is the state indicator, which equals one during bad economic states and zero otherwise. Panel A employs NBER-dated recessions to define bad states following Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011). Panel B defines bad states using the bottom third of sorted rates of real GDP growth following Rapach, Strauss, and Zhou (2010). Panel C defines bad states as periods in which the Purchasing Managers Index is below the threshold value of 44.48 specified as in Berge and Jordà (2011). Panel D defines bad states as periods in which cyclical consumption is more than one standard deviation below its mean. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values. The sample covers the period from 1953Q4 to 2017Q4.

	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
			Panel A: NBER Business Cycle Dates			
β_{bad}	-0.83	-3.85	-3.53	-3.01	-5.86	-7.01
	(-1.86)**	(-2.91)***	(-2.09)***	(-2.39)***	(-4.91)***	(-3.74)***
β_{good}	-0.37	-1.26	-2.45	-3.15	-3.84	-4.71
	(-2.61)***	(-2.93)***	(-3.76)***	(-4.12)***	(-4.17)***	(-3.97)***
	[3.22]	[14.42]	[18.69]	[22.14]	[32.07]	[35.01]
			Panel B: Real GDP Growth			
β_{bad}	-0.76	-2.61	-3.08	-3.24	-4.54	-5.95
	(-3.56)***	(-4.41)***	(-3.84)***	(-4.32)***	(-5.73)***	(-5.01)***
β_{good}	-0.24	-1.00	-2.30	-3.07	-3.84	-4.50
	(-1.37)*	(-2.35)**	(-3.35)***	(-3.88)***	(-3.65)***	(-3.30)***
	[3.99]	[13.95]	[18.74]	[22.15]	[31.46]	[34.84]
			Panel C: Purchasing Managers Index (PMI)			
β_{bad}	-0.90	-5.02	-5.71	-5.26	-7.24	-7.66
	(-1.61)*	(-6.07)***	(-3.91)***	(-3.74)***	(-3.80)***	(-3.12)**
β_{good}	-0.38	-1.29	-2.33	-2.97	-3.82	-4.77
	(-2.73)***	(-3.05)***	(-3.70)***	(-4.18)***	(-4.30)***	(-3.93)***
	[3.14]	[15.56]	[20.50]	[22.94]	[32.76]	[35.03]
			Panel D: Cyclical Consumption			
β_{bad}	-0.46	-1.17	-1.58	-2.61	-2.75	-3.92
	(-2.15)**	(-2.34)**	(-2.18)**	(-3.22)***	(-2.88)**	(-3.12)***
β_{good}	-0.38	-1.88	-3.44	-3.60	-5.21	-5.81
	(-1.79)**	(-2.86)***	(-3.34)***	(-2.94)***	(-3.35)***	(-3.09)***
	[2.80]	[11.48]	[19.97]	[22.50]	[33.08]	[34.97]

Table IV
Alternative Detrending Methods

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log excess return on the CRSP value-weighted index, and cc_t is one-quarter-lagged cyclical consumption. We compute cc by fitting a linear, linear with a break, quadratic, or cubic time trend specification as indicated in the first column. The stochastic method computes cyclical consumption as a five-year backward-looking moving average. For each regression, the table reports the slope estimate, Newey-West corrected t-statistic in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values. The sample covers the period from 1953Q4 to 2017Q4.

	$h = 1$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Linear	-0.22	-0.83	-1.43	-1.87	-2.40	-2.77
	(-2.63)***	(-2.89)***	(-2.90)***	(-3.21)***	(-3.28)***	(-2.68)**
	[1.49]	[5.76]	[9.29]	[11.70]	[14.69]	[13.44]
Break	-0.62	-2.35	-3.99	-5.05	-6.00	-6.46
	(-3.37)***	(-3.30)***	(-3.63)***	(-4.78)***	(-5.50)***	(-4.52)***
	[3.54]	[13.15]	[22.36]	[28.67]	[33.87]	[29.92]
Quadratic	-0.44	-1.64	-2.69	-3.21	-3.66	-3.62
	(-2.50)**	(-2.60)***	(-2.61)***	(-2.87)***	(-3.25)***	(-2.85)***
	[1.79]	[7.03]	[11.07]	[12.44]	[13.28]	[9.61]
Cubic	-0.83	-3.24	-5.55	-6.84	-8.00	-8.59
	(-3.51)***	(-3.78)***	(-4.29)***	(-5.90)***	(-6.28)***	(-4.84)***
	[3.87]	[15.27]	[26.44]	[32.54]	[37.66]	[33.20]
Stochastic	-1.09	-4.60	-8.57	-11.62	-15.26	-18.88
	(-1.92)*	(-3.08)***	(-3.67)***	(-5.18)***	(-6.42)***	(-6.15)***
	[1.35]	[7.11]	[14.87]	[22.11]	[31.90]	[36.29]

Table V
Predictive Regressions for Subsamples

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log excess return on the S&P 500 index or the CRSP value-weighted index, and cc_t is one-quarter-lagged cyclical consumption. The sample of returns covers the period from 1980Q1 to 2017Q4 (Panel A), 1990Q1 to 2017Q4 (Panel B), and 2000Q1 to 2017Q4 (Panel C). For each regression, the table reports the slope estimate, Newey-West corrected t-statistic in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values.

	$h = 1$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
			Panel A: Post-1980 Period			
SP500	-0.35	-1.34	-2.53	-3.43	-4.55	-5.55
	(-2.24)**	(-2.96)***	(-3.10)***	(-3.25)***	(-3.52)***	(-3.70)***
	[2.22]	[9.21]	[17.92]	[23.26]	[30.42]	[33.27]
CRSP	-0.35	-1.30	-2.31	-2.98	-3.91	-4.61
	(-2.11)**	(-2.80)***	(-2.89)***	(-3.03)***	(-3.45)***	(-3.76)***
	[1.86]	[7.90]	[15.48]	[19.44]	[26.35]	[27.54]
			Panel B: Post-1990 Period			
SP500	-0.44	-1.67	-3.00	-4.13	-5.61	-7.09
	(-2.52)***	(-3.07)***	(-2.82)***	(-3.20)***	(-3.74)***	(-4.58)***
	[3.83]	[14.35]	[21.34]	[26.99]	[36.29]	[40.49]
CRSP	-0.42	-1.53	-2.59	-3.43	-4.69	-5.85
	(-2.25)***	(-2.64)***	(-2.34)***	(-2.62)***	(-3.29)***	(-4.43)***
	[2.96]	[11.16]	[16.44]	[20.53]	[29.89]	[33.20]
			Panel C: Post-2000 Period			
SP500	-0.54	-2.06	-3.28	-4.06	-4.91	-6.31
	(-2.94)***	(-3.40)***	(-2.93)***	(-3.35)***	(-4.62)***	(-6.95)***
	[7.35]	[23.72]	[30.40]	[37.38]	[47.44]	[55.64]
CRSP	-0.52	-1.92	-2.83	-3.33	-3.99	-5.14
	(-2.58)***	(-2.86)***	(-2.33)**	(-2.57)***	(-3.58)**	(-5.41)***
	[5.56]	[18.30]	[21.66]	[25.70]	[34.79]	[42.77]

Table VI
Benchmark Out-of-Sample Tests

The table presents results of out-of-sample forecasts of h-quarter-ahead log excess returns on the CRSP value-weighted index, where a time-varying expected returns model with cyclical consumption as regressor is compared against a constant expected returns model. The parameters used to calculate cyclical consumption are estimated recursively from the current latest-available consumption data. R^2_{OOS} is the out-of-sample R^2 in percent. ENC-NEW is the encompassing test statistic of Clark and McCracken (2001) and MSE-F is the F-statistic of McCracken (2007). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to one-sided wild bootstrap p-values in the case of the ENC-NEW and MSE-F statistics and according to the Clark and West (2007) test in the case of the R^2_{OOS} statistic. The first observation in the out-of-sample period is 1980Q1, 1990Q1, or 2000Q1, and the predictive model is estimated recursively until 2017Q4.

	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A: Forecasting from 1980						
ENC-NEW	2.85***	12.73***	25.26***	35.79***	54.53***	60.56***
MSE-F	0.98***	6.43***	17.09***	30.17***	42.93***	41.07***
R^2_{OOS}	0.64*	4.14***	10.55***	17.63***	23.86***	23.59***
Panel B: Forecasting from 1990						
ENC-NEW	3.51***	13.77***	22.47***	29.46***	46.57***	53.95***
MSE-F	2.24***	9.76***	17.63***	26.92***	44.09***	52.80***
R^2_{OOS}	1.96*	8.22***	14.37***	21.05***	31.25***	36.21***
Panel C: Forecasting from 2000						
ENC-NEW	2.40***	7.89***	11.76***	17.01***	29.89***	39.64***
MSE-F	0.99***	4.15***	5.85***	10.97***	20.33***	33.08***
R^2_{OOS}	1.35	5.67***	8.26***	15.24***	26.29***	38.43***

Table VII
Portfolios Sorted on Industry

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log excess portfolio return, and cc_t is one-quarter-lagged cyclical consumption. The table reports results for industry categories including Nondurable Goods (NON), Durable Goods (DUR), Manufacturing (MAN), Energy (ENG), HiTech Business Equipment (HT), Telephone and Television Transmission (TEL), Wholesale and Retail (SHOPS), Healthcare and Medical Equipment (HLTH), Utilities (UTILS), and Other industry categories (OTHER). For each regression, the table reports the slope estimate, Newey-West corrected t-statistic in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values. The sample covers the period from 1953Q4 to 2017Q4.

	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
NON	-0.31	-1.12	-1.94	-2.54	-3.47	-4.51
	(-2.25)**	(-2.42)***	(-2.70)***	(-2.72)***	(-2.82)***	(-2.81)**
	[1.63]	[6.40]	[10.71]	[14.24]	[19.95]	[23.97]
DUR	-0.66	-2.36	-3.71	-4.47	-5.69	-6.99
	(-3.47)***	(-4.31)***	(-5.17)***	(-6.18)***	(-6.62)***	(-6.36)***
	[4.07]	[13.38]	[19.44]	[26.59]	[35.94]	[39.88]
MAN	-0.39	-1.40	-2.15	-2.42	-3.12	-3.84
	(-2.61)***	(-3.07)***	(-3.34)***	(-3.55)***	(-3.27)***	(-2.91)***
	[2.11]	[7.97]	[12.55]	[14.57]	[20.19]	[21.21]
ENG	-0.18	-0.68	-0.93	-0.56	-0.69	-1.26
	(-1.22)	(-1.36)	(-1.05)	(-0.50)	(-0.56)	(-0.88)
	[0.18]	[1.49]	[1.68]	[0.26]	[0.56]	[2.22]
HT	-0.62	-2.35	-4.04	-5.23	-6.85	-8.29
	(-2.93)***	(-3.42)***	(-3.72)***	(-4.68)***	(-5.18)***	(-5.03)***
	[3.42]	[12.04]	[18.81]	[23.12]	[32.31]	[34.21]
TEL	-0.46	-1.74	-3.24	-4.29	-5.19	-5.89
	(-3.11)***	(-3.19)***	(-3.22)***	(-3.23)***	(-3.19)***	(-2.87)***
	[3.99]	[11.74]	[18.48]	[21.10]	[23.34]	[22.74]
SHOPS	-0.42	-1.49	-2.32	-2.91	-3.97	-5.05
	(-2.76)***	(-3.19)***	(-3.43)***	(-3.46)***	(-3.52)***	(-3.37)***
	[2.28]	[8.83]	[12.16]	[15.81]	[23.39]	[26.96]
HLTH	-0.37	-1.38	-2.48	-3.45	-4.92	-6.48
	(-2.48)***	(-2.85)***	(-2.76)***	(-2.87)***	(-3.28)***	(-3.61)***
	[1.92]	[8.01]	[12.67]	[16.02]	[23.69]	[30.01]
UTILS	-0.31	-1.24	-2.17	-2.56	-3.11	-3.54
	(-2.81)***	(-3.55)***	(-3.92)***	(-3.41)***	(-3.04)***	(-2.46)**
	[2.20]	[9.49]	[16.84]	[18.15]	[20.41]	[20.26]
OTHER	-0.43	-1.64	-2.75	-3.53	-4.74	-5.95
	(-2.66)***	(-3.36)***	(-4.31)***	(-4.90)***	(-4.42)***	(-3.90)***
	[2.23]	[8.87]	[14.66]	[18.89]	[26.28]	[29.99]

Table VIII
Alternative Consumption Measures

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log excess return on the CRSP value-weighted index, and cc_t is one-quarter-lagged cyclical consumption. We compute cc by applying the robust linear projection method of Hamilton (2018) to the logarithm of real per capita consumption expenditures for nondurable goods (NON), services (SERV), durable goods (DUR), the stock of durable goods (SDUR), nondurable and durable goods (GOODS), or aggregate personal consumption expenditures (PCE) as indicated in the first column. For each regression, the table reports the slope estimate, Newey-West corrected t-statistic in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values. The sample covers the period from 1953Q4 to 2017Q4.

	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
NON	-0.38	-1.44	-2.50	-3.22	-4.28	-5.14
	(-3.04)***	(-3.73)***	(-3.95)***	(-4.65)***	(-5.93)***	(-6.58)***
	[3.18]	[11.83]	[21.14]	[28.51]	[42.41]	[45.42]
SERV	-0.38	-1.39	-2.33	-2.80	-3.57	-4.33
	(-2.84)***	(-3.33)***	(-3.72)***	(-4.16)***	(-4.05)***	(-3.51)***
	[2.66]	[9.42]	[15.90]	[18.58]	[24.81]	[26.51]
DUR	-0.07	-0.29	-0.58	-0.82	-1.06	-1.28
	(-1.79)**	(-2.49)***	(-3.24)***	(-3.79)***	(-4.24)***	(-4.59)***
	[0.96]	[5.85]	[14.31]	[23.25]	[33.33]	[37.79]
SDUR	-0.10	-0.39	-0.79	-1.10	-1.39	-1.61
	(-1.99)**	(-2.38)***	(-3.05)***	(-3.47)***	(-3.81)***	(-3.98)***
	[1.16]	[5.86]	[14.44]	[22.82]	[30.62]	[31.66]
GOODS	-0.17	-0.69	-1.30	-1.76	-2.31	-2.79
	(-2.42)***	(-3.02)***	(-3.49)***	(-4.02)***	(-4.70)***	(-5.16)***
	[1.93]	[8.57]	[18.05]	[27.12]	[39.67]	[43.78]
PCE	-0.29	-1.08	-1.91	-2.48	-3.20	-3.91
	(-2.85)***	(-3.20)***	(-3.80)***	(-4.36)***	(-4.58)***	(-4.45)***
	[2.72]	[9.93]	[18.58]	[25.41]	[35.40]	[39.37]

Table IX
International Evidence

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log return on world or regional MSCI total equity indices, and cc_t is one-quarter-lagged global cyclical consumption. We compute global cyclical consumption as the cross-country average for 20 developed countries, including Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. For each regression, the table reports the slope estimate, Newey-West corrected t-statistic in parentheses (h lags), and adjusted-R^2 in percent in square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to one-sided wild bootstrap p-values. We consider the longest possible sample period for each set of test asset returns. The sample of returns on the aggregate G7 index covers the period from 1977Q1 to 2017Q4 and from 1970Q1 to 2017Q4 otherwise.

	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
World	-0.48	-1.95	-3.53	-4.73	-5.78	-6.32
	(-3.59)***	(-4.04)***	(-4.63)***	(-5.33)***	(-6.51)***	(-7.35)***
	[5.32]	[22.47]	[37.46]	[46.75]	[53.97]	[51.86]
World ex USA	-0.48	-1.96	-3.55	-4.76	-5.79	-6.23
	(-3.56)***	(-3.90)***	(-4.18)***	(-4.52)***	(-5.20)***	(-5.33)***
	[4.87]	[19.73]	[33.05]	[41.82]	[48.06]	[44.70]
EAFE	-0.51	-2.01	-3.62	-4.90	-6.07	-6.74
	(-3.65)***	(-3.82)***	(-4.00)***	(-4.21)***	(-4.74)***	(-5.18)***
	[5.24]	[19.70]	[32.09]	[40.50]	[47.14]	[46.73]
Europe	-0.51	-2.08	-3.78	-5.07	-6.16	-6.67
	(-3.75)***	(-4.11)***	(-4.35)***	(-4.64)***	(-5.22)***	(-5.31)***
	[5.54]	[21.68]	[35.69]	[44.11]	[49.99]	[47.14]
Far East	-0.51	-2.11	-3.85	-5.06	-6.03	-6.33
	(-2.97)***	(-3.65)***	(-3.63)***	(-3.53)***	(-3.54)***	(-3.14)***
	[3.38]	[13.88]	[22.58]	[27.17]	[30.66]	[26.76]
Pacific	-0.49	-2.03	-3.65	-4.77	-5.66	-5.94
	(-3.07)***	(-3.68)***	(-3.60)***	(-3.41)***	(-3.36)***	(-2.98)***
	[3.63]	[14.78]	[23.85]	[28.54]	[31.21]	[27.06]
G7	-0.44	-1.86	-3.51	-4.83	-5.91	-6.50
	(-3.13)***	(-3.66)***	(-4.18)***	(-4.85)***	(-6.11)***	(-7.40)***
	[5.14]	[22.80]	[40.93]	[50.31]	[56.95]	[55.14]

Table X
Out-of-sample Results with Alternative Predictor Variables

The table presents the out-of-sample R^2 statistics in percent from h-quarter-ahead forecasts of log excess returns on the CRSP value-weighted index, where the time-varying expected returns model with one of the predictive variables listed as a regressor in the second column is compared against a constant expected returns model. Section IV contains definitions of the forecasting variables. The parameters used to calculate variables 17 to 20 are estimated recursively from the current latest-available data. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, according to the Clark and West (2007) test statistics. The first observation in the out-of-sample period is 1980Q1; the predictive model is estimated recursively until 2017Q4.

#	var	$h=1$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
1	dp	-5.29	-23.40	-49.33	-40.09	-30.04	-40.84
2	dy	-6.45	-21.81	-41.22	-33.53	-25.92	-39.13
3	e/p	-2.63	-10.62	-22.59	-21.79	-27.60	-37.16
4	d/e	-3.30	-5.77	-8.57	-15.48	-10.88	-8.36
5	$svar$	-17.32	-17.82	-18.72	-25.54	-18.04	-24.82
6	b/m	-1.72	-6.12	-15.93	-20.37	-24.04	-28.74
7	$ntis$	-2.51	-13.75	-9.92	-9.37	-15.42	-31.11
8	tbl	-4.03	-11.83	-5.78	-25.16	-64.17	-127.11
9	lty	-2.45	-9.93	-13.35	-38.98	-75.43	-133.55
10	ltr	-1.55	-2.12	-1.58	-3.86	-7.58	-9.14
11	tms	-2.78	-0.93	10.31***	12.77***	13.88***	5.32***
12	dfy	-2.70	-4.90	-3.29	-15.30	-21.02	-16.52
13	dfr	-0.49	-2.48	-3.94	-6.80	-9.24	-12.59
14	$infl$	-1.86	-0.84	1.20**	-6.36	-10.65	-22.00
15	i/k	0.23	2.21**	8.79***	16.76***	27.39***	24.88***
16	s^w	-3.17	-9.69	-17.69	-30.03	-39.36	-45.37
17	cay	-2.18	-13.33	-20.03	-15.01	-10.90	-24.23
18	σ_c	-0.44	0.06	-3.69	-13.05	-10.67	-10.49
19	gap	-2.02	-5.51	-4.45	-1.47	7.50***	9.69***
20	cc	0.64*	4.14***	10.55***	17.63***	23.86***	23.59***

Table XI
Summary Statistics of Simulated and Historical Data

The table presents summary statistics for log consumption growth (Δc) and log aggregate stock market returns (r) expressed in annualized percentages. It reports the time-series averages (E), standard deviations (σ), and Sharpe ratios computed as the mean excess return ($r - r_f$) divided by the standard deviation. In the model, $r - r_f$ is the log return on the consumption or dividend claim minus the log risk-free rate. In the data, $r - r_f$ is the log return on the value-weighted CRSP index minus the log Treasury bill return. Statistics reported in the columns "Consumption claim" and "Dividend claim" present the moments in the simulated data. We generate 1,000,000 quarterly observations based on the calibrated parameter values of Campbell and Cochrane (1999). The column "Actual data" summarizes the moments in our empirical sample covering the period from 1947Q1 to 2017Q4.

Statistic	Consumption claim	Dividend claim	Actual data
$E(\Delta c)$	1.89	1.89	1.89
$\sigma(\Delta c)$	1.50	1.50	1.00
$E(r - r_f)/\sigma(r - r_f)$	0.43	0.38	0.40
$E(r - r_f)$	5.22	5.01	6.52
$\sigma\left(r - r^f\right)$	12.02	13.31	16.38

Table XII
Model-Implied Predictability

Panel A of the table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter-ahead log excess market return, and cc_t is one-quarter-lagged cyclical consumption computed as specified in equations (1) and (11) in the actual and simulated data for $k = 24$, respectively. For each regression, the table reports the slope estimate and the adjusted-R^2 in percent in square brackets. The rows "Consumption claim" and "Dividend claim" present results from 1,000,000 quarterly simulated observations. The row "Actual data" displays results from the historical data. Panel B of the table presents results of out-of-sample forecasts of h-quarter ahead log excess stock returns, where the time-varying expected returns model with cyclical consumption as regressor is compared against a constant expected returns model. The rows "Consumption claim" and "Dividend claim" show average out-of-sample R^2s in percent in simulated data from 2,500 artificial samples of size 284, which matches the number of observations in our post-war sample. For each artificial sample, we compute 112-(h-1) out-of-sample forecasts for consistency with the number of forecasts in the post-1990 evaluation window. The row "Actual data" presents the corresponding results from the historical data.

	$h = 1$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Panel A: In-Sample Predictability						
Consumption claim	-0.22	-0.82	-1.51	-2.10	-2.60	-3.04
	[1.75]	[6.53]	[12.02]	[16.59]	[20.48]	[23.80]
Dividend claim	-0.22	-0.82	-1.52	-2.11	-2.61	-3.05
	[1.46]	[5.36]	[9.68]	[13.13]	[15.90]	[18.13]
Actual data	-0.42	-1.55	-2.57	-3.13	-4.08	-5.01
	[3.16]	[11.43]	[18.68]	[22.46]	[31.53]	[34.46]
Panel B: Out-of-Sample Predictability						
Consumption claim	1.00	3.47	5.99	7.56	8.54	9.51
Dividend claim	0.68	2.15	3.18	3.26	2.69	1.71
Actual data	1.96	8.22	14.37	21.05	31.25	36.21

Figure 1. Cyclical consumption. The figure plots the series of cyclical consumption along with NBER recessions represented by shaded bars over the period from 1953Q4 to 2017Q4.