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The predictive power of cyclical consumption for stock market returns in the Nordic countries

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Abstract

In this paper, I show that cyclical deviations from the long-term growth trend of consumption give useful information on future stock market returns in the Nordic countries. In-sample predictive regressions show significant negative correlations between the cyclical component of consumption and future returns across all Nordic markets. However, one-quarter-ahead out-of-sample tests suggest the cyclical consumption model outperforms a historical average forecast only in Finland. The in-sample results are economically sizable and robust to a number of alternative detrending methods.

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I. Introduction

The relationship between numerous business cycle variables and expected stock returns is a topic extensively covered in financial literature. The general understanding is that equity premia vary over time, reflecting the underlying macroeconomic changes in business cycles. E.g. Campbell (1987), Fama and French (1989), Yogo (2006), and Smith, Sorensen, and Wickens (2010) find strong evidence of countercyclicality in expected returns. In the context of consumption, expected returns are rationalized to be low in good economic states, since the lower marginal utility of present-day consumption renders investing excess cash more attractive, thus driving up stock prices and decreasing returns. In bad economic states, expected returns need to rise in order to match the relatively high marginal utility of present-day consumption.[1]

Atanasov, Møller, and Priestley (2020) propose a new business cycle variable, cyclical consumption, which has economically sizable predictive properties for aggregate stock market returns. They find that cyclical consumption, referred to as cc, provides better information on expected returns than many other popular predictive variables previously presented in literature, including various ones derived from consumption, such as those in Lettau and Ludvigson (2001), Santos and Veronesi (2006), and Bansal, Khatchatrian, and Yaron (2005). Their benchmark in-sample and out-of-sample tests show strong evidence of predictability with U.S. data. Additionally, they find the predictive power of cc to be prominent across industry portfolios and international markets. Interestingly, they also find that the predictability is not limited to bad economic states, which stands in contrast with existing literature that generally struggles to find equal predictability in good times.[2]

In this paper, I extend the pioneering work of Atanasov, Møller, and Priestley (2020) by examining the predictive properties of cyclical consumption for aggregate stock market returns in the Nordic countries. The rest of the paper is structured as follows: In Section II, I detrend the consumption data using the linear projection method of Hamilton (2018). In Section III, I present the in-sample predictive regression results for each Nordic country. Section IV examines the recursive one-step-ahead out-of-sample predictive properties of cc. Section V assesses the robustness to other detrending methods. Finally, Section VI concludes.

[1] See e.g. Campbell and Cochrane (1999) and Atanasov, Møller, and Priestley (2020).

[2] Atanasov, Møller, and Priestley (2020) point to Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018).

II. Detrending the Consumption Data

As household consumption data are often reported in various accounts by type or durability, the first issue involves the choice of consumption accounts to be included in the analysis. I follow Atanasov, Møller, and Priestley (2020) by focusing on aggregated quarterly consumption data on non-durable goods and services. All data are seasonally adjusted and in local currencies. The Finnish data are also working day adjusted, at reference year 2010 prices and provided by Statistics Finland. The Swedish data are in 2018 constant prices and are downloaded from Statistics Sweden. The Danish data, provided by Statistics Denmark, are in reference year 2010 chained values. The Norwegian data, presented in 2017 fixed prices, are downloaded from Statistics Norway. Finally, the Icelandic data are in reference year 2005 chained volume estimates, downloaded from OECD. I divide the aggregate consumption figures by corresponding quarterly population provided by the statistics bureaus of each country to form a measure of per capita consumption expenditure.

The extraction of the cyclical component of a time series can be achieved using various methods. Atanasov, Møller, and Priestley (2020) examine the effects of the choice of method by comparing five alternative detrending models, including a linear trend model, a linear trend model allowing for a breakpoint, a quadratic model, a cubic model, and a stochastic model following Campbell (1991) and Hodrick (1992) to their benchmark choice of the linear projection method of Hamilton (2018). They find strong evidence of in-sample predictability with all detrending methods, and thus argue that the choice of method has no crucial effect on the outcome of the predictive regressions. I present regression results with other detrending methods in Section V.

Hamilton (2018) proposes an approach for decomposing a time series into its trend and cycle component in a manner that ensures the preservation of the underlying dynamic relations and the applicability for numerous different data-generating processes. The approach involves regression of the y variable on a constant and p-number of consecutive lagged observations of y, the closest being k quarters prior. For quarterly data, Hamilton (2018) recommends values of $p = 4$ and $k = 8$ for business cycle related research and advocates the use of p and k values that are integer multiples of four. I follow Atanasov, Møller, and Priestley (2020) in choosing to use $p = 4$ lags, and in Section III, I present regression results with k values ranging from 4 to 32.

The formulation of the detrending method follows that of Atanasov, Møller, and Priestley (2020):

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

where c_t is the log of the consumption measure at time t and the following c variables indicate the lagged log consumption values at times $t-k$, $t-k-1$, $t-k-2$, and $t-k-3$ respectively. The obtained residuals reveal the distance to the long-term trend and are therefore used as the measure of the cyclical component of consumption, cc.

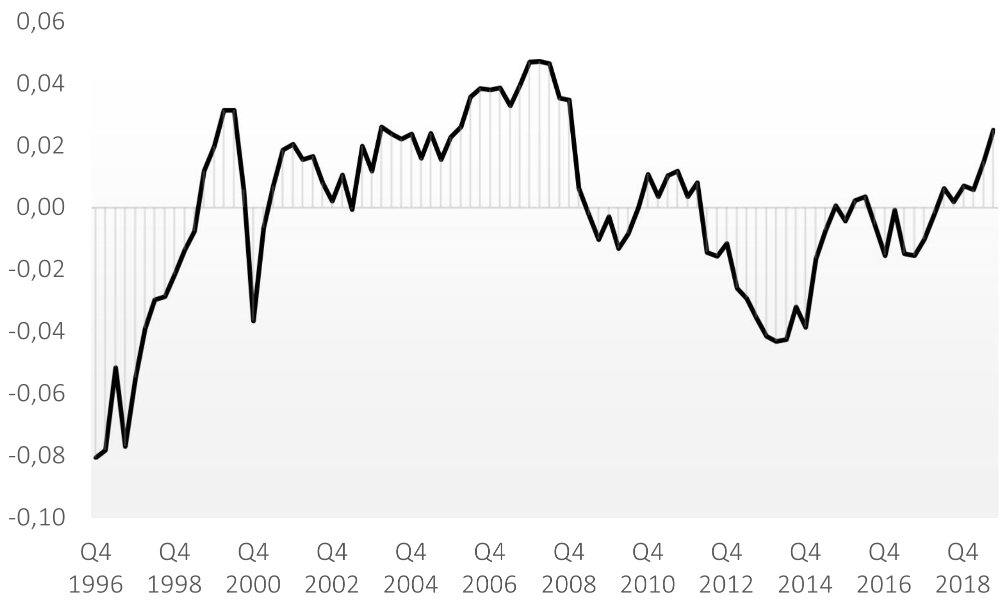

Figure I. Example of a cyclical consumption cc time series. The figure presents a time series of cyclical consumption between Q4 1996 and Q3 2019 in Finland, detrended using the Hamilton (2018) method described in equation (1) for $k = 24$.

Figure I presents a visualization of a cc time series obtained by detrending consumption data using the Hamilton (2018) method. The graph represents the fluctuations of cc around its mean of 0, calculated with Finnish consumption data for $k = 24$. The findings are consistent with those of Atanasov, Møller, and Priestley (2020), in a sense that cc rises through economic expansions, such as the period prior to the 2008 financial crisis, and falls through economic contractions, e.g. in 2009 and through the European debt crisis. The lowest values of cc are found in the aftermath of the early 1990s depression in Finland with clear upward trends following both the 1990s depression and the recovery from the European debt crisis. For comparison, cc graphs for Sweden, Denmark, and Norway are presented in Appendix A.

III. In-Sample Predictability

To examine the in-sample predictive power of cyclical consumption for stock market returns in the Nordic countries, I download quarterly price index data on the main stock exchange in each country from Thomson Reuters Datastream. In most cases, the price index time series data extend further back beyond the base date of the consumption data and/or the quarterly population data provided by the statistics bureaus, thus rendering the first few datapoints of the price index data unusable. For example, in Finland the available price index data extend back to Q1 1987, whereas quarterly consumption data are available from Q1 1990 onwards.

The indices used include OMXH price index for Finland, OMXS price index for Sweden, OMXC price index for Denmark, Oslo SE OBX price index for Norway, and OMX Iceland All Share price index for Iceland. In this paper, I focus on predictability for market returns. For reference, Atanasov, Møller, and Priestley (2020) find even stronger in-sample predictability for excess returns over the risk-free rate with U.S. data.

I follow Atanasov, Møller, and Priestley (2020) by employing a simple predictive regression model to assess the in-sample predictive properties of cc:

$$r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}, \tag{2}$$

where $r_{t,t+h}$ is the accumulated log market return over a period of h quarters ahead, calculated from time t, and cc_t is the cyclical consumption at time t.

Following Atanasov, Møller, and Priestley (2020), I calculate the t-statistics using the Newey and West (1987) estimator, which produces a covariance matrix that better accounts for heteroskedasticity and autocorrelation.[3] To calculate empirical p-values, Atanasov, Møller, and Priestley (2020) also choose to employ an adaptation of a wild bootstrap simulation originally proposed by Wu (1986), which they argue produces a better approximation of the slope estimate distribution. In this paper however, I choose to omit the bootstrap procedure due to a great number of the Newey-West t-stat values already suggesting very strong statistical significance in the in-sample regressions. The p-values are calculated to test a null hypothesis of no predictability against a one-sided alternative hypothesis, since the direction of the

[3] I use a truncation lag corresponding to the value of h in each regression. As in Atanasov, Møller, and Priestley (2020), the choice of truncation lag does not alter the results by a significant amount.

departure from the null can be economically motivated within reason prior to the analysis.[4] Formally:

$$H_0: \beta = 0$$

$$H_1: \beta < 0$$

Table I presents the predictive regression results with Finnish consumption and stock market data. The OLS estimates of β indicate an inverse relationship between cc and market returns. The results are generally statistically significant at longer prediction horizons and with greater values of k used in the detrending procedure. The significance diminishes at smaller value combinations of h and k and, perhaps more interestingly, when k exceeds 28. Generally, the statistical significance grows stronger as the prediction horizon is extended further, which is in line with the benchmark in-sample findings of Atanasov, Møller, and Priestley (2020), who show similar patterns with U.S. data. They identify the choice of $k = 24$, or six years, as a good benchmark, which the Finnish data supports.[5]

Another finding is that the adjusted R^2 generally grows as the prediction horizon is extended further. This phenomenon is backed by existing literature, e.g. Fama and French (1988), who find similar results studying the predictive power of dividend yields for expected stock returns. The adjusted R^2s suggest the in-sample predictive power of cc for stock market returns is economically sizable.[6] The in-sample regression results obtained using the Finnish data lead to the rejection of the null hypothesis of no predictability with combinations of greater values for h and k.

Interestingly, the in-sample predictive regression results for Sweden in Table II suggest that the predictability exists in a noticeably different region of h and k combinations. While evidence of predictability and negative slope estimates with statistical significance even at the 1% level can be found, in stark contrast to the Finnish results, the greatest R^2 values are observed with smaller values of the detrending k, particularly with $k = 4$ and $k = 8$. The R^2 values exhibit a pronounced peak at return prediction horizons of two to three years, unlike in Finland, where the predictive power does not drop off at longer horizons.

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[4] See e.g. Inoue and Kilian (2005).
[5] To verify that my methods are consistent with those of Atanasov, Møller, and Priestley (2020), I replicate some of their benchmark return predictive regressions with U.S. data. The results are presented in Appendix B.
[6] According to e.g. Atanasov, Møller, and Priestley (2020) & Campbell and Thompson (2008).

Table I: Predictability for Market Returns in Finland

Table I presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Finland. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the Finnish data begins in Q1 1990 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	0.37	-1.05	-3.32	-2.37	-6.12	-8.08	-12.18
	(0.59)	(-0.57)	(-1.10)	(-0.63)	(-1.69) **	(-1.57) *	(-2.35) **
	[-0.66]	[-0.48]	[1.26]	[-0.23]	[3.14]	[5.16]	[11.81]
k = 8	-0.93	-2.25	-2.31	-3.77	-7.53	-10.74	-14.56
	(-1.86) **	(-1.27)	(-0.84)	(-1.27)	(-2.25) **	(-2.96) ***	(-3.32) ***
	[1.39]	[2.10]	[0.56]	[1.86]	[8.05]	[14.91]	[26.45]
k = 12	-0.09	-0.30	-2.31	-4.59	-8.92	-12.08	-15.87
	(-0.22)	(-0.19)	(-0.97)	(-1.64) *	(-3.74) ***	(-5.20) ***	(-6.84) ***
	[-0.96]	[-0.94]	[1.09]	[4.64]	[16.15]	[27.17]	[48.50]
k = 16	-0.51	-2.87	-7.14	-11.38	-16.42	-21.22	-17.32
	(-0.81)	(-1.55) *	(-2.53) ***	(-4.27) ***	(-4.69) ***	(-5.79) ***	(-8.35) ***
	[-0.30]	[4.19]	[14.03]	[25.08]	[43.45]	[67.41]	[64.57]
k = 20	-0.87	-3.56	-7.93	-11.41	-15.96	-14.54	-12.24
	(-1.26)	(-1.79) **	(-3.63) ***	(-4.96) ***	(-5.41) ***	(-7.60) ***	(-11.16) ***
	[1.48]	[8.57]	[21.61]	[32.19]	[55.03]	[60.22]	[64.68]
k = 24	-1.03	-4.72	-8.80	-12.69	-11.41	-10.25	-9.14
	(-2.19) **	(-3.03) ***	(-3.33) ***	(-3.56) ***	(-4.48) ***	(-7.39) ***	(-5.67) ***
	[2.25]	[15.18]	[27.22]	[43.10]	[43.01]	[45.08]	[46.06]
k = 28	-1.20	-4.20	-8.67	-7.03	-6.30	-6.06	-6.83
	(-1.82) **	(-2.21) **	(-2.70) ***	(-2.85) ***	(-3.54) ***	(-2.26) **	(-2.69) ***
	[3.19]	[11.68]	[27.42]	[18.81]	[17.81]	[16.54]	[26.11]
k = 32	-1.63	-4.74	-3.56	-2.23	-2.21	-4.26	-3.35
	(-2.23) **	(-1.70) **	(-1.14)	(-0.72)	(-0.56)	(-0.96)	(-0.81)
	[6.66]	[14.14]	[4.83]	[0.89]	[0.75]	[6.30]	[4.51]

The differences between the results in Finland and the results in Sweden could be explained by several factors. First, the sample period for the Swedish data begins in Q2 1993, whereas the Finnish sample period has a starting point of Q1 1990. However, as shown in Appendix C, once the sample periods of Finland, Sweden and Norway are standardized to match the one in Denmark, the Swedish data still exhibits strongest predictability with shorter detrending horizons.

Table II: Predictability for Market Returns in Sweden

Table II presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Sweden. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the Swedish data begins in Q2 1993 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	-0.36	-8.26	-21.27	-29.87	-27.33	-22.25	-17.16
	(-0.26)	(-1.89) **	(-4.64) ***	(-4.63) ***	(-4.80) ***	(-4.64) ***	(-5.89) ***
	[-0.96]	[7.65]	[29.14]	[44.27]	[34.94]	[24.93]	[28.36]
k = 8	-1.77	-10.35	-19.19	-20.61	-16.55	-9.86	-6.61
	(-1.96) **	(-4.17) ***	(-6.39) ***	(-5.57) ***	(-6.33) ***	(-3.36) ***	(-1.62) *
	[3.02]	[26.31]	[51.42]	[48.56]	[30.57]	[14.19]	[10.10]
k = 12	-2.12	-9.19	-14.08	-12.07	-4.76	0.28	0.66
	(-2.72) ***	(-3.47) ***	(-4.35) ***	(-5.59) ***	(-1.95) **	(0.07)	(0.16)
	[6.58]	[27.97]	[37.43]	[22.80]	[3.09]	[-1.43]	[-1.39]
k = 16	-1.83	-7.92	-9.91	-2.61	4.00	5.98	2.42
	(-1.71) **	(-2.54) ***	(-3.42) ***	(-1.04)	(0.94)	(1.23)	(0.77)
	[4.22]	[18.67]	[16.48]	[-0.24]	[1.46]	[6.14]	[0.40]
k = 20	-2.21	-7.30	-2.12	5.10	9.62	6.36	2.99
	(-2.16) **	(-2.04) **	(-0.50)	(0.93)	(1.33)	(1.08)	(0.90)
	[4.71]	[11.03]	[-0.75]	[1.54]	[10.95]	[5.30]	[0.64]
k = 24	0.35	0.41	4.03	8.09	6.24	3.71	2.16
	(0.28)	(0.07)	(0.46)	(0.79)	(0.69)	(0.50)	(0.40)
	[-1.19]	[-1.34]	[0.13]	[4.30]	[2.61]	[0.07]	[-1.07]
k = 28	-0.77	-2.31	-3.50	-6.50	-7.07	-7.75	-7.54
	(-0.57)	(-0.41)	(-0.53)	(-0.97)	(-1.08)	(-1.48) *	(-1.64) *
	[-0.85]	[-0.44]	[-0.09]	[3.60]	[4.73]	[6.35]	[7.64]
k = 32	-0.33	-5.85	-13.40	-15.63	-13.30	-11.27	-8.57
	(-0.20)	(-1.15)	(-2.46) ***	(-2.43) ***	(-2.41) ***	(-2.40) **	(-1.83) **
	[-1.36]	[6.30]	[24.48]	[31.78]	[22.35]	[16.23]	[12.42]

One possible explanation for the differing patterns observed in the Swedish regressions is related to the overall length of the sample period. Atanasov, Møller, and Priestley (2020) report their benchmark predictive regression results in the U.S. for $k = 24$ with a sample period beginning in Q4 1953 and ending in Q4 2017, where the number of observations is in the region of 250. With the limited data in Sweden, regressions with $k = 24$ result in values of n between 55 and 78, which in turn might lead to results that are not representative of the true data-generating process in the long run.

Table III: Predictability for Market Returns in Denmark

Table III presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Denmark. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the Danish data begins in Q1 1996 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	-1.08	-4.15	-1.26	-4.37	-9.43	-12.89	-12.51
	(-1.46) *	(-1.35) *	(-0.33)	(-1.52) *	(-5.10) ***	(-12.19) ***	(-13.68) ***
	[1.26]	[5.68]	[-0.93]	[2.10]	[12.86]	[26.04]	[32.32]
k = 8	-0.60	-0.76	0.06	-4.16	-9.71	-11.58	-10.52
	(-1.13)	(-0.41)	(0.02)	(-1.41) *	(-4.59) ***	(-7.59) ***	(-6.36) ***
	[0.07]	[-0.90]	[-1.35]	[3.34]	[21.59]	[35.33]	[35.46]
k = 12	-0.10	-1.19	-2.45	-7.63	-11.40	-11.90	-10.41
	(-0.20)	(-0.52)	(-0.74)	(-2.79) ***	(-6.13) ***	(-8.77) ***	(-5.43) ***
	[-1.24]	[0.02]	[1.36]	[19.12]	[42.37]	[50.09]	[47.40]
k = 16	-0.41	-2.45	-5.04	-9.78	-12.35	-11.96	-9.43
	(-0.78)	(-0.98)	(-1.60) *	(-4.52) ***	(-8.10) ***	(-10.78) ***	(-5.19) ***
	[-0.34]	[4.98]	[11.75]	[40.28]	[57.45]	[56.46]	[41.97]
k = 20	-0.70	-3.70	-6.89	-10.94	-12.58	-10.76	-6.69
	(-1.08)	(-1.45) *	(-2.89) ***	(-5.57) ***	(-7.32) ***	(-8.57) ***	(-3.14) ***
	[1.59]	[12.60]	[24.48]	[49.17]	[56.64]	[42.32]	[18.73]
k = 24	-1.42	-5.97	-9.12	-13.06	-13.39	-9.99	-4.89
	(-2.46) ***	(-2.52) ***	(-4.25) ***	(-5.56) ***	(-5.68) ***	(-5.70) ***	(-1.39) *
	[8.85]	[27.96]	[31.73]	[52.11]	[47.56]	[27.00]	[5.50]
k = 28	-1.76	-7.59	-10.78	-14.88	-13.95	-7.80	-9.93
	(-2.49) ***	(-2.53) ***	(-4.13) ***	(-4.55) ***	(-5.80) ***	(-1.53) *	(-2.57) ***
	[9.17]	[28.98]	[26.93]	[41.28]	[33.35]	[8.74]	[14.39]
k = 32	-1.93	-7.84	-9.47	-14.30	-13.68	-15.39	-15.83
	(-2.39) **	(-2.12) **	(-3.14) ***	(-4.21) ***	(-4.96) ***	(-6.54) ***	(-7.92) ***
	[8.82]	[24.76]	[15.16]	[33.59]	[23.84]	[29.75]	[28.30]

Table III presents the in-sample predictive regression results for Denmark. The negative correlation between cc and market returns is significant across the vast majority of detrending and forecasting horizons. The results are overall very similar to the ones in Finland, with greater value combinations of h and k showing stronger predictability and statistical significance. However, much like the R^2s in the regressions with the Swedish data in Table II, the model exhibits stronger explanatory power at prediction horizons of three to four years, with the R^2s of longer horizons generally decreasing from those levels.

Table IV: Predictability for Market Returns in Norway

Table IV presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Norway. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the Norwegian data begins in Q2 1987 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	1.24	-0.45	-1.61	-3.74	-2.16	-6.22	-2.42
	(1.05)	(-0.19)	(-0.37)	(-0.80)	(-0.45)	(-1.39) *	(-0.57)
	[0.50]	[-0.81]	[-0.57]	[0.57]	[-0.46]	[2.91]	[-0.19]
k = 8	0.80	-0.08	-2.44	-3.21	-5.18	-4.98	-2.50
	(1.06)	(-0.03)	(-0.53)	(-0.71)	(-1.29)	(-1.20)	(-0.71)
	[0.15]	[-0.88]	[0.33]	[1.05]	[4.14]	[3.46]	[0.57]
k = 12	0.09	-1.61	-3.60	-6.36	-5.59	-5.37	-4.64
	(0.15)	(-0.64)	(-1.01)	(-1.98) **	(-1.77) **	(-1.70) **	(-1.62) *
	[-0.88]	[0.41]	[3.12]	[10.80]	[7.51]	[6.35]	[7.03]
k = 16	-0.12	-1.71	-5.09	-5.87	-5.18	-5.68	-5.99
	(-0.19)	(-0.86)	(-1.74) **	(-2.07) **	(-1.72) **	(-1.62) *	(-2.07) **
	[-0.89]	[0.89]	[8.76]	[10.59]	[7.37]	[8.39]	[14.10]
k = 20	-0.63	-3.38	-4.93	-5.83	-5.97	-6.92	-5.56
	(-1.10)	(-1.62) *	(-1.74) **	(-1.97) **	(-1.92) **	(-2.34) **	(-2.38) ***
	[0.08]	[6.25]	[7.98]	[10.26]	[10.10]	[13.71]	[12.50]
k = 24	-0.01	-1.78	-3.66	-5.36	-5.71	-4.70	-4.79
	(-0.02)	(-0.73)	(-1.06)	(-1.63) *	(-2.05) **	(-1.78) **	(-1.90) **
	[-1.00]	[0.77]	[3.27]	[7.25]	[8.31]	[5.20]	[6.83]
k = 28	0.24	-1.93	-4.80	-6.80	-5.30	-5.38	-3.03
	(0.41)	(-0.78)	(-1.41) *	(-2.34) **	(-2.08) **	(-1.68) **	(-0.75)
	[-0.91]	[0.94]	[5.96]	[12.13]	[6.76]	[6.06]	[1.67]
k = 32	-0.37	-2.84	-6.43	-6.45	-6.01	-3.71	-1.45
	(-0.57)	(-1.08)	(-1.95) **	(-2.54) ***	(-2.18) **	(-0.83)	(-0.26)
	[-0.79]	[2.89]	[11.19]	[10.50]	[7.76]	[1.90]	[-0.76]

The regression results for Norway, presented in Table IV, show noticeably less pronounced results than the other countries, in terms of the slope estimates and their statistical significance, and the R^2s. This is an interesting observation, considering the sample period for Norway is the longest of all countries studied in this paper. With the standardized comparable sample periods beginning in Q1 1996 presented in Appendix C, however, the Norwegian results gain substantially more predictive power across longer prediction and detrending horizons, with the estimated coefficients on cc increasing in size and significance. It seems that the choice of sample period can easily lead to different levels of observed predictability.

Table V: Predictability for Market Returns in Iceland

Table V presents a 7 x 7 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Iceland. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the Icelandic data begins in Q4 2009 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	-0.10	-0.50	-5.37	-8.49	-5.54	0.95	4.48
	(-0.16)	(-0.40)	(-7.19) ***	(-15.29) ***	(-1.51) *	(0.75)	(12.55)
	[-3.26]	[-3.06]	[33.63]	[51.87]	[7.01]	[-8.07]	[24.34]
k = 8	-0.41	-2.08	-4.91	-6.01	-6.05	1.88	-0.20
	(-1.25)	(-3.47) ***	(-12.17) ***	(-10.14) ***	(-7.37) ***	(2.11)	(-0.42)
	[0.23]	[24.39]	[82.19]	[54.99]	[43.48]	[-8.10]	[-32.96]
k = 12	-0.60	-1.61	-3.36	-2.20	0.26	1.74	NA
	(-1.52) *	(-2.68) ***	(-3.89) ***	(-2.43) **	(0.21)	(4.22)	NA
	[3.95]	[8.47]	[30.35]	[-2.10]	[-14.14]	[-0.33]	NA
k = 16	-1.08	-4.61	-4.40	-5.67	-3.45	NA	NA
	(-1.92) **	(-2.86) ***	(-4.54) ***	(-4.24) ***	(-8.78) ***	NA	NA
	[6.59]	[38.77]	[44.80]	[21.03]	[33.71]	NA	NA
k = 20	0.13	4.24	1.69	7.10	NA	NA	NA
	(0.08)	(3.44)	(2.69)	(12.00)	NA	NA	NA
	[-7.09]	[31.68]	[8.23]	[59.06]	NA	NA	NA
k = 24	1.43	3.26	0.63	NA	NA	NA	NA
	(0.44)	(1.74)	(0.69)	NA	NA	NA	NA
	[-7.64]	[-4.29]	[-32.42]	NA	NA	NA	NA
k = 28	5.87	-53.13	NA	NA	NA	NA	NA
	(0.41)	(-12.44) ***	NA	NA	NA	NA	NA
	[-12.89]	[66.77]	NA	NA	NA	NA	NA

Statistics Iceland began publishing quarterly population figures in 2010, which means that cc cannot be calculated in per capita terms prior to that point in time. Table V presents the predictive regression results in Iceland. A group of statistically significant negative slope estimates with sizable R^2 values is observable, although suspect to e.g. the small sample biases identified by Nelson and Kim (1993), undermining the reliability of the estimates.

In summary, the in-sample regression results in the Nordic countries support the findings of Atanasov, Møller, and Priestley (2020), generally leading to the rejection of the null hypothesis of no predictability. Cyclical consumption has extensive in-sample predictive power for stock market returns across all Nordic markets, with statistically significant negative correlations reported between the two, suggesting that expected market returns are high in times when consumption lies below its long-term trend and vice versa. However, the regressions also suggest that it is not always possible to identify a universally valid detrending k to be used in the Hamilton (2018) method, as shown by the regressions with Swedish data. The predictability grows stronger as the prediction horizon is extended beyond one quarter, supporting the findings of e.g. Fama and French (1988).

IV. Out-of-Sample Predictability

Atanasov, Møller, and Priestley (2020) point out that to potentially benefit from the predictive models in the form of, e.g., an active trading strategy, one has to predict the future market returns using only the information available up to that specific point of time. Furthermore, even strong evidence of predictability obtained from full in-sample predictive regressions does not necessarily imply that the results hold out-of-sample. This is supported by e.g. Sullivan, Timmermann, and White (1999), Bossaerts and Hillion (1999), and Welch and Goyal (2008), who generally find little to no evidence of out-of-sample predictability, even when corresponding in-sample regressions suggest otherwise.

To avoid the effects of the forward-looking bias present in the in-sample predictive regressions, I follow Atanasov, Møller, and Priestley (2020) by performing a set of one-step-ahead predictive regressions to assess the out-of-sample predictive properties of cyclical consumption. I begin by dividing the data used in Section III into initial in-sample periods of R observations (excluding the first $k = 24$ observations lost to the Hamilton (2018) detrending procedure) and out-of-sample periods during which the one-quarter ahead forecasts are made. The first out-of-sample forecast is therefore for the observation indexed $R + 1$, using the coefficients estimated with the first R observations. The regression is then repeated recursively for the remaining observations, each time using all the data available to that point of time.

I follow Atanasov, Møller, and Priestley (2020) and compare the prediction errors from the out-of-sample cc model to those from a model that predicts future returns solely based on a historical average up to that point in time.[7] I calculate the ENC-NEW test statistic of Clark and McCracken (2001) to test the null hypothesis that the unrestricted cc model is encompassed by the historical average model, i.e. it does not provide additional information compared to its restricted counterpart. Additionally, I compute the MSE-F statistic of McCracken (2007) to test

[7] Welch & Goyal (2008) advocate the use of a historical mean forecast as comparison to the unrestricted model.

Table VI: Out-of-Sample Performance

Table VI presents one-quarter-ahead out-of-sample predictive regression test statistics for Finland, Sweden, Denmark and Norway. The test statistics compare the recursive cyclical consumption prediction model with cc detrended using Hamilton (2018) with $k = 24$, against a model predicting returns based on a recursive historical average forecast. R indicates the size of the initial in-sample period in quarters. ENC-NEW test statistics of Clark and McCracken (2001) are associated with *, and ** to indicate the test statistic being greater than its critical value for 90th and 95th percentile, respectively.[8] MSE-F statistics of McCracken (2007) are associated with *, **, and *** to indicate the test statistic being greater than its critical value for 90th, 95th, and 99th percentile, respectively. The out-of-sample R^2s presented in percent are calculated following Campbell and Thompson (2008).

Panel A: Finland, Q1 1990 - Q3 2019							
	R = 48	*R = 52*	*R = 56*	*R = 60*	*R = 64*	*R = 68*	*R = 72*
ENC-NEW	1.47 *	1.42 *	1.49 *	1.34 *	3.67 **	3.12 **	1.28 **
MSE-F	0.80 *	0.28	0.67	0.38	3.43 ***	3.34 ***	1.29 **
R^2_{OOS}	1.78	0.70	1.83	1.16	10.92	12.21	6.06
Panel B: Sweden, Q2 1993 - Q3 2019							
	R = 48	*R = 52*	*R = 56*	*R = 60*	*R = 64*	*R = 68*	*R = 72*
ENC-NEW	-0.56	-0.26	0.83 *	0.83 *	0.67 *	0.56 *	0.26
MSE-F	-5.85	-4.32	-1.21	-0.23	-0.33	-0.16	0.04
R^2_{OOS}	-23.28	-19.06	-5.54	-1.25	-2.28	-1.46	0.56
Panel C: Denmark, Q1 1996 - Q3 2019							
	R = 48	*R = 52*	*R = 56*	*R = 60*	*R = 64*	*R = 68*	*R = 72*
ENC-NEW	1.19 *	1.49 **	0.75 *	1.35 **	0.26	NA	NA
MSE-F	-6.23	-7.27	-6.63	-3.35	-1.50	NA	NA
R^2_{OOS}	-45.23	-83.18	-123.44	-72.01	-60.01	NA	NA
Panel D: Norway, Q2 1987 - Q3 2019							
	R = 48	*R = 52*	*R = 56*	*R = 60*	*R = 64*	*R = 68*	*R = 72*
ENC-NEW	0.53	0.54	0.78	-0.37	-0.49	0.01	-0.86
MSE-F	-0.73	-0.42	0.21	-2.55	-2.68	-1.76	-3.79
R^2_{OOS}	-1.34	-0.84	0.45	-6.31	-7.38	-5.28	-13.94

the null hypothesis that the mean squared errors from the historical average model are smaller than those of the cc model. Finally, I calculate the out-of-sample R^2 following Campbell and Thompson (2008).

Table VI presents the test statistics comparing the out-of-sample predictive cc model and the model based on historical average forecast. Interpreting the negative MSE-F and OOS R^2 test

[8] Clark and McCracken (2004) note that the F-type test statistics like ENC-NEW and MSE-F benefit from the utilization of a simulation method, e.g. a bootstrap procedure, when conducting inference. Such analysis is not necessarily of interest here, however, since the negative MSE-F & R^2_{OOS} statistics for the majority of comparisons already indicate that the historical average model outperforms the cc model in most cases.

statistics, the historical average forecasts outperform the cc model in one-quarter-ahead prediction across Sweden, Denmark and Norway Interestingly, however, the cyclical consumption model does significantly better in the Finnish sample, especially in the initial in-sample period range of 64 – 72 quarters. In that range, the OOS R^2s reach sizable levels as well, although still being generally smaller than their in-sample counterparts.

In their OOS tests, Atanasov, Møller, and Priestley (2020) find that with CRSP index data, the cc model consistently outperforms the historical average model across different forecasting periods. It must be noted, however, that they operate with a significantly larger sample, which not only allows for a longer in-sample period yielding more precise first estimates, but also longer forecasting periods that result in less imprecise test statistics. It might be, that given a longer dataset, the OOS results with Nordic data would look noticeably different.

Atanasov, Møller, and Priestley (2020) also calculate the OOS test statistics for prediction horizons longer than one quarter and find even better cc forecasting ability relative to the historical average model. Experiments with longer prediction horizons using the Nordic datasets showed the deterioration of the cc model in comparison with the historical average model, suggesting the relationship exists inversely as well, when the historical average forecast does better than the cc model in a given set of data. In addition, extending the prediction horizon reduces the amount of usable observations, further rendering the small sample OOS results more imprecise.

V. Robustness to the Choice of Detrending Method

Atanasov, Møller, and Priestley (2020) note that it is not clear which detrending method should be used in the context of extracting cyclicality from consumption data. Following them, I examine the effects of detrending method selection on in-sample predictability by repeating the regressions in Section III with cyclical consumption measures obtained through a secular linear time trend regression, as well as a quadratic and a cubic regression. In addition, I also follow Campbell (1991) and Hodrick (1992) in computing the cyclical consumption stochastically at time t as a difference between the log consumption at time t and a mean of the log consumption values from the time period 20 quarters, or five years, prior.

Table VII: In-Sample Regressions with Other Detrending Methods

Table VII presents in-sample regression results from the predictive model described in equation (2) using alternative detrending methods. The rows indicate the choice of cyclical consumption detrending method. Following the equations (5), (7), and (8) in Atanasov, Møller, and Priestley (2020), LIN indicates the cc equalling the residuals from a linear time trend model $c_t = d_0 + d_1 t + \omega_t$, QUAD indicates the residuals from the quadratic time trend model $c_t = d_0 + d_1 t + d_2 t^2 + \omega_t$, and CUB indicates the residuals from the cubic time trend model $c_t = d_0 + d_1 t + d_2 t^2 + d_3 t^3 + \omega_t$. STOCH indicates the stochastic five-year moving average method following Campbell (1991) and Hodrick (1992). The columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for each country is identical to that in Section III.

Panel A: Finland

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
LIN	-0.48	-2.63	-6.05	-8.89	-12.55	-16.48	-19.43
	(-1.35) *	(-1.93) **	(-2.83) ***	(-3.57) ***	(-4.75) ***	(-8.37) ***	(-14.31) ***
	[0.31]	[6.52]	[16.67]	[25.50]	[42.18]	[59.47]	[73.20]
QUAD	-1.30	-5.83	-10.50	-11.64	-13.18	-15.75	-16.54
	(-3.01) ***	(-3.78) ***	(-4.17) ***	(-3.73) ***	(-2.95) ***	(-3.26) ***	(-3.86) ***
	[3.36]	[17.42]	[27.05]	[24.18]	[26.35]	[31.63]	[31.13]
CUB	-1.00	-5.26	-10.16	-11.45	-14.20	-18.55	-21.66
	(-1.89) **	(-2.70) ***	(-3.14) ***	(-3.43) ***	(-3.39) ***	(-4.03) ***	(-5.69) ***
	[1.07]	[10.25]	[18.22]	[16.81]	[22.17]	[31.02]	[36.00]
STOCH	0.75	1.35	0.79	0.00	-3.07	-7.03	-7.55
	(1.02)	(0.52)	(0.17)	(-0.00)	(-0.78)	(-2.16) **	(-2.89) ***
	[0.25]	[-0.09]	[-0.97]	[-1.18]	[0.04]	[4.54]	[7.06]

Panel B: Sweden

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
LIN	-0.87	-4.22	-8.51	-10.55	-9.22	-7.50	-6.47
	(-1.69) **	(-2.07) **	(-3.16) ***	(-3.86) ***	(-2.23) **	(-1.42) *	(-1.26)
	[1.75]	[10.66]	[21.87]	[23.29]	[14.94]	[9.18]	[8.03]
QUAD	-1.20	-7.93	-13.17	-8.96	1.76	9.33	12.55
	(-1.13)	(-1.96) **	(-2.26) **	(-1.34) *	(0.25)	(1.12)	(1.24)
	[0.34]	[10.33]	[15.39]	[4.59]	[-0.94]	[4.14]	[10.27]
CUB	-1.64	-10.23	-17.74	-14.49	-3.86	3.82	6.86
	(-1.46) *	(-2.60) ***	(-2.92) ***	(-2.24) **	(-0.61)	(0.47)	(0.63)
	[1.20]	[15.21]	[24.26]	[11.55]	[-0.35]	[-0.44]	[1.55]
STOCH	-0.90	-5.51	-11.43	-13.29	-10.30	-8.29	-8.83
	(-0.95)	(-2.21) **	(-3.01) ***	(-3.18) ***	(-2.87) ***	(-2.35) **	(-3.53) ***
	[0.44]	[10.30]	[25.98]	[30.44]	[19.25]	[13.57]	[23.60]

Panel C: Denmark							
	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
LIN	-0.63	-3.02	-4.36	-6.05	-8.34	-8.13	-6.57
	(-1.38) *	(-1.24)	(-1.44) *	(-2.65) ***	(-4.05) ***	(-3.80) ***	(-2.50) ***
	[1.11]	[8.07]	[9.85]	[17.40]	[28.82]	[27.29]	[21.72]
QUAD	-0.66	-3.70	-5.66	-8.80	-12.16	-12.80	-11.81
	(-1.38) *	(-1.29)	(-1.53) *	(-3.62) ***	(-5.08) ***	(-6.74) ***	(-9.07) ***
	[0.53]	[7.64]	[10.01]	[22.59]	[37.89]	[42.03]	[42.02]
CUB	-0.47	-2.92	-4.25	-7.52	-10.47	-10.85	-9.23
	(-0.74)	(-0.84)	(-0.99)	(-2.05) **	(-2.62) ***	(-3.80) ***	(-3.94) ***
	[-0.39]	[3.66]	[4.57]	[14.63]	[25.30]	[28.04]	[25.34]
STOCH	-0.23	-1.88	-3.33	-5.94	-9.45	-11.14	-11.58
	(-0.46)	(-0.89)	(-0.93)	(-1.83) **	(-4.37) ***	(-7.49) ***	(-9.72) ***
	[-1.11]	[2.04]	[4.32]	[14.45]	[34.85]	[50.87]	[65.46]
Panel D: Norway							
	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
LIN	0.16	-0.70	-1.74	-2.14	-2.11	-2.36	-2.77
	(0.36)	(-0.36)	(-0.51)	(-0.57)	(-0.61)	(-0.75)	(-0.93)
	[-0.71]	[-0.42]	[0.46]	[0.82]	[0.78]	[1.03]	[2.73]
QUAD	0.77	-1.34	-1.72	-3.55	-5.86	-7.05	-6.35
	(0.77)	(-0.48)	(-0.35)	(-0.65)	(-1.33) *	(-1.83) **	(-1.83) **
	[-0.11]	[-0.24]	[-0.29]	[1.25]	[5.27]	[7.60]	[8.77]
CUB	0.87	-1.64	-2.97	-4.91	-6.54	-7.17	-6.37
	(0.90)	(-0.56)	(-0.56)	(-0.85)	(-1.39) *	(-1.72) **	(-1.63) *
	[-0.12]	[-0.18]	[0.35]	[2.09]	[4.71]	[5.48]	[5.97]
STOCH	0.85	0.13	-2.12	-3.79	-3.50	-2.64	-2.19
	(1.34)	(0.09)	(-0.62)	(-0.99)	(-0.92)	(-0.77)	(-0.82)
	[0.44]	[-0.95]	[0.20]	[2.31]	[1.56]	[0.27]	[0.15]
Panel E: Iceland							
	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
LIN	-0.73	-2.81	-5.41	-4.38	1.64	3.15	5.87
	(-1.29)	(-2.34) **	(-5.16) ***	(-3.33) ***	(1.13)	(2.02)	(26.04)
	[2.23]	[24.52]	[56.15]	[18.38]	[-0.27]	[22.08]	[78.91]
QUAD	-0.98	-3.38	-7.11	-7.61	3.95	5.46	8.42
	(-1.67) *	(-2.66) ***	(-7.64) ***	(-5.68) ***	(2.48)	(2.35)	(15.55)
	[3.42]	[22.60]	[63.12]	[32.00]	[4.01]	[24.53]	[59.30]
CUB	-1.49	-3.39	-5.05	-0.60	9.54	6.55	-0.87
	(-2.05) **	(-1.78) **	(-1.78) **	(-0.24)	(7.62)	(5.10)	(-0.44)
	[5.45]	[13.11]	[17.77]	[-3.67]	[57.25]	[39.59]	[-6.36]
STOCH	-1.68	-4.51	-4.53	-5.40	-3.46	NA	NA
	(-3.14) ***	(-2.48) **	(-7.80) ***	(-4.37) ***	(-4.42) **	NA	NA
	[28.66]	[43.15]	[75.12]	[44.12]	[-19.05]	NA	NA

The results presented in Table VII reflect the predictive performance of cyclical consumption detrended using the Hamilton (2018) method in Section III. The alternative methods generally do well in Finland and Denmark, where the predictability is strong with the Hamilton (2018) method as well, whereas the Norwegian data shows weaker signs of predictability, just as in the benchmark regressions. The Swedish results mirror the ones in Section III in a sense that the predictability is relatively stronger with shorter prediction horizons. The Icelandic data is once again suspect to small sample imprecisions.

Overall, I arrive at the same conclusion as Atanasov, Møller, and Priestley (2020) by concluding that the choice of detrending method seems to be generally irrelevant. However, smaller sample sizes do seem to have an effect on the perceived prediction power of cc, since the results presented in Table VII are significantly more inconsistent across different markets and prediction horizons than those of Atanasov, Møller, and Priestley (2020), who operate with a broad U.S. sample extending back to 1953.

VI. Conclusion

In this paper, I extend the work of Atanasov, Møller, and Priestley (2020), by examining the predictive properties of their new predictive variable, cyclical consumption, in the Nordic markets. In-sample regressions with cyclical consumption detrended using the Hamilton (2018) method show strong evidence of predictability in all Nordic countries. Comparisons between different prediction horizons suggest that the predictability grows stronger when the prediction horizon is increased, supporting the findings of e.g. Fama and French (1988).

In a robustness test, I follow Atanasov, Møller, and Priestley (2020) by comparing the effects of alternative detrending methods of cyclical consumption on in-sample predictability. The results with a linear, a quadratic and a cubic time trend model as well as the stochastic model of Campbell (1991) and Hodrick (1992), show similar patterns of predictability as the benchmark results with the Hamilton (2018) method. This supports the findings of Atanasov, Møller, and Priestley (2020) by suggesting the choice of detrending method is generally irrelevant.

As e.g. Bossaerts and Hillion (1999), and Welch and Goyal (2008) point out that out-of-sample predictability cannot be assumed based on in-sample results, I conduct a set of out-of-sample tests to assess the recursive one-quarter-ahead predictive power of cyclical consumption, based only on data available at the time of the forecast. The cyclical consumption model outperforms the historical average forecast only in Finland, while producing greater mean squared errors than the historical average model across other Nordic countries. Accurate out-of-sample analysis requires a greater number of observations than its in-sample counterpart, however, leaving the results suspect to imprecisions.

Overall, the evidence provided in this paper suggests that the inverse, predictive relationship between cyclical consumption and expected stock market returns exists in the Nordic countries as well. This is in line with the findings of e.g. Campbell and Cochrane (1999) and Atanasov, Møller, and Priestley (2020), in a sense that cyclical deviations from the long-term growth trend of consumption give useful information on expected stock market returns.

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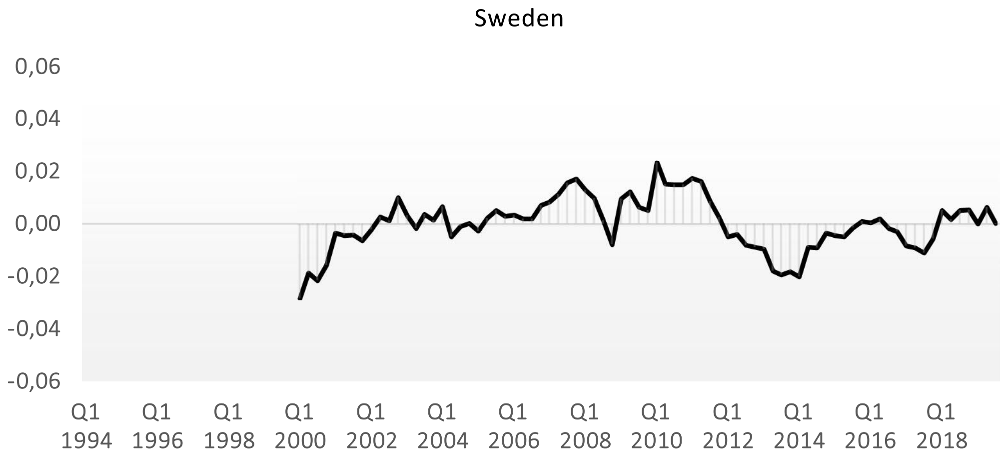
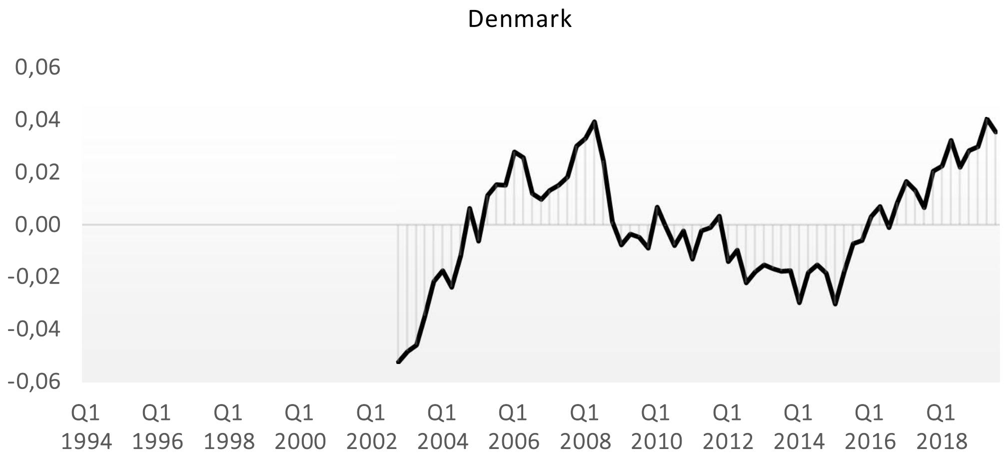
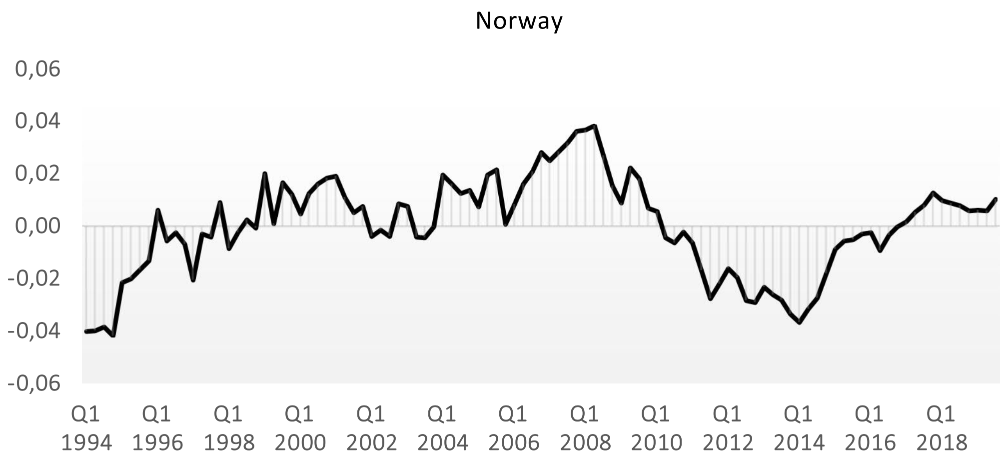
Appendix A: Cyclical Consumption Figures

Appendix A presents cyclical consumption time series for Sweden, Denmark and Norway. As in Figure I in Section II, the consumption data is detrended using the Hamilton (2018) method, with $k = 24$. With $k = 24$, the Icelandic cc time series contains only 13 data points and is therefore not presented here.







Appendix B: In-Sample Regressions with U.S. Data

Table VIII: Predictability for Market Returns in the U.S.

Table VIII presents regression results from the predictive model described in equation (2) with U.S. cyclical consumption data downloaded from the U.S. Bureau of Economic Analysis and S&P500 return data downloaded from the Wharton Research Data Services database. The detrending k used in the Hamilton (2018) method described in equation (1) in Section II equals 24. The columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the U.S data begins in Q1 1947 and ends in Q4 2017, with the first 27 observations lost in detrending.

Panel A: Excess Market Returns over Risk Free Rate							
	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 24	-0.44	-1.65	-2.83	-3.53	-4.53	-5.52	-5.64
	(-3.29) ***	(-3.88) ***	(-4.36) ***	(-4.81) ***	(-4.74) ***	(-4.26) ***	(-3.58) ***
	[3.65]	[12.85]	[20.96]	[24.89]	[32.04]	[34.22]	[30.00]
Panel B: Market Returns							
	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 24	-0.35	-1.33	-2.21	-2.66	-3.51	-4.45	-4.64
	(-2.68) ***	(-3.08) ***	(-3.25) ***	(-3.35) ***	(-3.43) ***	(-3.34) ***	(-2.92) ***
	[2.35]	[8.66]	[13.57]	[15.17]	[20.78]	[24.07]	[21.88]

To assess the methods used in this paper, e.g. the piece of code created to run the regressions, I replicate some of the benchmark return predictive regressions with U.S. data reported in Table I of Atanasov, Møller, and Priestley (2020). I follow Atanasov, Møller, and Priestley (2020) in downloading seasonally adjusted consumption data on non-durables and services from the National Income and Product Accounts Table 7.1, which is provided by the U.S. Bureau of Economic Analysis, and the Standard and Poor's composite stock price index data from the Wharton Research Data Services database.

The replicated regression results presented in Table VIII deviate slightly from those of Atanasov, Møller, and Priestley (2020), perhaps due to the unavailability of the exact 2009 chain-weighted-dollar dataset they use as a measure of consumption. The data used here is in 2012 chain-weighted dollars.

Appendix C: Identical Sample Period Regressions

Table IX: Predictability for Market Returns in Finland, Q1 1996 – Q3 2019

Table IX presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Finland. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the data begins in Q1 1996 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	0.36	-1.14	-4.48	-2.82	-4.77	-9.83	-9.08
	(0.34)	(-0.37)	(-1.08)	(-0.70)	(-1.39) *	(-2.99) ***	(-2.65) ***
	[-1.08]	[-0.99]	[0.51]	[-0.60]	[1.03]	[10.12]	[11.11]
k = 8	-0.69	-2.12	-2.38	-3.23	-8.06	-10.76	-9.08
	(-1.13)	(-0.88)	(-0.61)	(-0.91)	(-2.46) ***	(-3.04) ***	(-2.58) ***
	[-0.58]	[0.10]	[-0.15]	[0.59]	[11.04]	[20.44]	[17.71]
k = 12	-0.56	-1.77	-3.77	-6.83	-10.46	-13.88	-12.52
	(-0.82)	(-0.57)	(-0.88)	(-2.32) **	(-5.23) ***	(-6.60) ***	(-4.73) ***
	[-0.83]	[-0.00]	[1.92]	[7.08]	[18.40]	[30.93]	[31.75]
k = 16	-0.68	-3.89	-8.13	-10.23	-14.23	-18.01	-15.42
	(-0.90)	(-1.09)	(-2.11) **	(-4.41) ***	(-9.70) ***	(-16.88) ***	(-10.15) ***
	[-0.49]	[5.57]	[15.31]	[22.90]	[42.48]	[65.16]	[58.31]
k = 20	-1.29	-6.02	-9.30	-11.29	-15.31	-17.51	-15.02
	(-1.46) *	(-1.81) **	(-2.79) ***	(-4.72) ***	(-8.50) ***	(-9.49) ***	(-10.38) ***
	[2.49]	[18.53]	[27.66]	[36.33]	[62.01]	[71.75]	[57.61]
k = 24	-1.52	-6.35	-9.39	-11.63	-14.73	-16.77	-12.87
	(-1.97) **	(-2.02) **	(-2.42) ***	(-3.34) ***	(-3.89) ***	(-4.67) ***	(-3.39) ***
	[5.19]	[21.73]	[28.20]	[38.22]	[54.41]	[58.66]	[33.02]
k = 28	-1.63	-7.34	-11.22	-12.22	-14.05	-14.07	-14.05
	(-2.12) **	(-2.15) **	(-2.66) ***	(-2.81) ***	(-3.06) ***	(-3.21) ***	(-4.00) ***
	[5.25]	[24.97]	[33.13]	[35.20]	[44.39]	[34.72]	[28.18]
k = 32	-2.02	-9.18	-13.14	-11.36	-10.93	-14.84	-13.32
	(-2.45) ***	(-2.68) ***	(-2.62) ***	(-2.02) **	(-2.09) **	(-2.65) ***	(-2.94) ***
	[8.03]	[31.88]	[34.63]	[26.08]	[23.96]	[30.87]	[20.12]

Table X: Predictability for Market Returns in Sweden, Q1 1996 – Q3 2019

Table X presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Sweden. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the data begins in Q1 1996 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	-0.43	-9.62	-23.85	-26.16	-21.73	-14.38	-16.54
	(-0.27)	(-2.23) **	(-5.11) ***	(-3.78) ***	(-4.39) ***	(-2.94) ***	(-3.90) ***
	[-1.08]	[8.52]	[31.34]	[33.39]	[24.26]	[11.37]	[27.26]
k = 8	-2.60	-14.65	-20.05	-18.17	-13.14	-11.95	-10.49
	(-3.11) ***	(-4.42) ***	(-4.62) ***	(-3.64) ***	(-3.79) ***	(-4.33) ***	(-3.78) ***
	[4.86]	[34.04]	[39.35]	[26.66]	[13.85]	[14.64]	[18.26]
k = 12	-3.04	-10.99	-13.80	-9.10	-5.56	-1.92	-3.65
	(-3.24) ***	(-3.26) ***	(-3.15) ***	(-2.19) **	(-1.78) **	(-0.35)	(-1.20)
	[7.27]	[20.32]	[16.36]	[5.17]	[1.22]	[-1.31]	[0.30]
k = 16	-2.46	-8.75	-9.85	-5.53	0.60	0.87	-1.33
	(-1.90) **	(-1.99) **	(-2.09) **	(-1.95) **	(0.11)	(0.16)	(-0.59)
	[3.89]	[12.58]	[8.27]	[1.84]	[-1.68]	[-1.75]	[-1.67]
k = 20	-1.90	-8.32	-10.79	-4.93	-1.16	-1.50	-1.82
	(-1.56) *	(-1.66) *	(-2.34) **	(-2.14) **	(-0.25)	(-0.48)	(-0.89)
	[1.60]	[9.76]	[10.79]	[0.84]	[-1.71]	[-1.73]	[-1.63]
k = 24	-2.59	-11.17	-12.79	-11.04	-7.65	-4.61	-4.57
	(-2.16) **	(-2.36) **	(-2.24) **	(-1.71) **	(-1.30) *	(-1.24)	(-1.52) *
	[4.92]	[21.31]	[15.23]	[10.47]	[4.12]	[0.54]	[0.30]
k = 28	-2.22	-10.30	-14.22	-12.08	-5.09	-3.11	-7.15
	(-1.70) **	(-2.10) **	(-2.30) **	(-1.64) *	(-0.92)	(-0.61)	(-1.72) **
	[2.83]	[17.39]	[19.52]	[15.73]	[2.10]	[-1.09]	[3.50]
k = 32	-3.52	-16.61	-20.53	-7.89	-1.73	-10.25	-9.12
	(-2.55) ***	(-2.96) ***	(-3.18) ***	(-1.75) **	(-0.21)	(-1.72) **	(-2.26) **
	[5.65]	[31.48]	[30.27]	[4.58]	[-2.02]	[7.68]	[4.38]

Table XI: Predictability for Market Returns in Norway, Q1 1996 – Q3 2019

Table XI presents a 7 x 8 matrix of regression results from the predictive model described in equation (2) with the cyclical consumption and market return data in Norway. The rows indicate the choice of cyclical consumption detrending k used in the Hamilton (2018) method described in equation (1) in Section II, while the columns represent the prediction horizon h in quarters. The slope estimate is presented for each regression, followed by the Newey-West test statistic in parentheses with the corresponding one-sided p-value indicated by *, **, and *** for 10%, 5%, and 1% significance level respectively. Finally, the adjusted R^2 in percent is reported in square brackets. The sample period for the data begins in Q1 1996 and ends in Q3 2019.

	h = 1	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*
k = 4	2.71	0.34	-7.58	-10.92	-10.99	-13.47	-9.31
	(1.80)	(0.09)	(-1.43) *	(-2.84) ***	(-3.11) ***	(-2.40) ***	(-2.00) **
	[3.47]	[-1.20]	[3.93]	[8.29]	[8.09]	[12.80]	[10.15]
k = 8	0.17	-3.95	-9.70	-11.43	-13.02	-12.52	-8.47
	(0.17)	(-1.12)	(-2.03) **	(-3.01) ***	(-2.90) ***	(-2.48) ***	(-2.33) **
	[-1.20]	[3.50]	[14.05]	[17.69]	[24.00]	[27.91]	[19.44]
k = 12	-0.46	-4.02	-8.17	-10.71	-11.17	-9.88	-7.06
	(-0.51)	(-1.15)	(-1.84) **	(-2.27) **	(-2.06) **	(-1.76) **	(-1.71) **
	[-0.94]	[5.26]	[12.94]	[19.44]	[23.32]	[20.52]	[16.20]
k = 16	-0.24	-3.42	-7.14	-8.02	-8.42	-8.08	-7.59
	(-0.30)	(-1.07)	(-1.73) **	(-1.85) **	(-1.69) **	(-1.58) *	(-2.14) **
	[-1.26]	[3.83]	[10.65]	[13.42]	[13.94]	[14.02]	[20.52]
k = 20	-0.64	-3.66	-6.87	-7.95	-9.36	-10.51	-9.06
	(-0.73)	(-1.01)	(-1.48) *	(-1.65) *	(-1.76) **	(-1.91) **	(-2.69) ***
	[-0.68]	[4.25]	[10.87]	[11.66]	[14.85]	[21.52]	[26.04]
k = 24	-0.87	-5.42	-9.12	-10.98	-13.15	-12.54	-10.66
	(-0.98)	(-1.36) *	(-1.51) *	(-1.78) **	(-2.05) **	(-2.05) **	(-3.92) ***
	[-0.15]	[10.57]	[14.98]	[17.75]	[25.35]	[27.67]	[34.70]
k = 28	-1.13	-6.65	-13.77	-16.30	-14.60	-11.59	-15.18
	(-1.18)	(-1.34) *	(-2.28) **	(-3.13) ***	(-3.87) ***	(-4.41) ***	(-9.84) ***
	[0.11]	[11.39]	[26.58]	[38.83]	[37.79]	[36.21]	[53.14]
k = 32	-0.83	-8.77	-17.90	-16.64	-11.45	-13.46	-13.55
	(-0.85)	(-1.76) **	(-5.31) ***	(-8.85) ***	(-4.30) ***	(-6.07) ***	(-12.53) ***
	[-0.97]	[17.30]	[44.55]	[48.72]	[34.46]	[41.85]	[42.67]