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Consumption growth and time-varying expected stock returns

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Abstract

When the consumption growth rate is measured based upon fourth quarter data, it tracks predictable variation in future excess stock returns. Low fourth quarter consumption growth rates predict high future excess stock returns such that expected returns are high at business cycle troughs and low at business cycle peaks. The consumption growth rate loses predictive power when it is measured based upon other quarters. This is consistent with the insight of Jagannathan and Wang (2007) that investors tend to review their consumption and investment plans during the end of each calendar year, and at possibly random times in between. The consumption growth rate measured based upon fourth quarter data is a much stronger predictive variable than benchmark predictive variables such as the dividend-price ratio, the term spread, and the default spread.

Keywords: Return predictability; Consumption growth
JEL codes: C12; E21; E44; G12

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1 Introduction

An extensive empirical literature in finance has demonstrated that expected stock returns vary over time. Campbell and Shiller (1988) and Fama and French (1988, 1989) among others use financial predictive variables based on stock and bond market data such as the dividend-price ratio, the term spread, and the default spread to document that stock returns display predictable variation over time. Fama and French (1989) link the financial predictive variables to the business cycle and suggest that investors require a higher expected return at a business cycle trough than they do at a business cycle peak. More recently, macro predictive variables such as the consumption-wealth ratio (Lettau and Ludvigson 2001) have been shown to predict stock returns providing a direct linkage between time-varying expected returns and the business cycle.[1]

This paper examines the ability of the consumption growth rate to capture predictable variation in stock returns over the business cycle. The consumption growth rate has a clear business cycle pattern and is closely related to the business cycles as measured by the National Bureau of Economic Research (NBER). To mitigate the effect of measurement error in consumption data as well as the effect of infrequent adjustment of consumption plans that may disrupt the linkage between the consumption growth rate and expected returns, I follow Jagannathan and Wang (2007) and measure the consumption growth rate based upon fourth quarter data. I examine the predictive power of the fourth quarter consumption growth rate by running regressions of future excess stock returns on the lagged fourth quarter consumption growth rate. I find strong support for the ability of the fourth quarter consumption growth rate to predict future excess stock returns using US post-war data from 1947 to 2005. The $\bar{R}^2$-statistic is as high as 19% at the 1-year horizon, and the slope estimate is strongly significantly negative such that low consumption growth rates predict high future excess stock returns. Hence, expected returns are high at business cycle troughs and low at business cycle peaks, which is consistent with the findings of Fama and French (1989). The fourth quarter consumption growth rate – a pure macroeconomic variable – is a much stronger predictive variable than the traditional financial predictive variables such as the dividend-price ratio, the term spread, and the default spread. In fact, the fourth quarter consumption growth rate drives out the financial predictive variables in multiple regressions. Moreover, the fourth quarter consumption growth rate also provides substantial additional information about future excess stock returns beyond that contained in the consumption-wealth ratio.

The consumption growth rate loses predictive power when it is measured based upon other quarters. This is consistent with the insight of Jagannathan and Wang (2007) that investors tend to review their consumption and investment plans during the end of each calendar year, and at possibly random times in between. Possible explanations include more leisure time during the Christmas holiday season, the resolution of uncertainty about end of year bonuses, and end of year tax consequences of portfolio choices; see Jagannathan and Wang (2007) and the references therein.

[1] See Cochrane (2007) for a comprehensive survey on the return predictability literature.

The fourth quarter consumption growth rate has a number of distinct properties as a predictive variable. First of all, the fourth quarter consumption growth rate is a pure macroeconomic variable that provides a direct linkage between time-varying expected returns and the business cycle. In addition, the fourth quarter consumption growth rate is easily constructed from the National Income and Product Accounts (NIPA) and does not rely on estimating a cointegration relationship (such as for example the consumption-wealth ratio). Finally, the fourth quarter consumption growth rate is an almost i.i.d. process and is much less persistent than alternative predictive variables. Given the controversy about return predictability using highly persistent predictive variables, it is noteworthy that the fourth quarter consumption growth rate – an almost i.i.d. process – can predict future stock returns.[2]

2 Data

The empirical analysis is based on US post-war data for the period 1947 to 2005. Consumption is measured as seasonally adjusted real per capita expenditures on non-durables and services. The consumption data is obtained from the National Income and Product Accounts (NIPA) and is available on quarterly frequency starting from 1947. The annual log excess stock return is calculated as the log return on the value weighted CRSP index including NYSE, AMEX, and NASDAQ firms minus the log return on a 3-month Treasury bill rate. As benchmark predictive variables, I use the log dividend-price ratio (dp_t), the term spread between long-term government bond yields and Treasury bill yields ($TERM_t$), the default spread between BAA and AAA corporate bond yields (DEF_t), and the consumption-wealth ratio ($\widehat{cay}_t$). dp_t is derived from CRSP value weighted returns with and without dividend capitalization. $TERM_t$, DEF_t, and $\widehat{cay}_t$ are obtained from Amit Goyal's website.

Table 1 provides summary statistics of the consumption growth rate. In the upper panel, the consumption growth rate is measured annually as year to year growth rates in quarterly consumption, i.e. 4Q-4Q is the consumption growth rate calculated from the fourth quarter in year $t-1$ to the fourth quarter in year t. In the lower panel, the consumption growth rate is measured quarterly, i.e. 3Q-4Q is the fourth quarter consumption growth rate calculated from the third quarter in year t to the fourth quarter in year t. The means and standard deviations of the year to year growth rates in quarterly consumption are similar across quarters, but the range is largest for the fourth quarter. This replicates the findings of Jagannathan and Wang (2007). Moreover, the quarterly consumption growth rate has a higher standard deviation and range in the fourth quarter compared to the first, second and third quarters.

Figure 1 plots the annual 4Q-4Q consumption growth rate and the quarterly 3Q-4Q consumption growth rate. The shaded areas represent the NBER recession dates. The annual 4Q-4Q consumption growth rate and the quarterly 3Q-4Q consumption growth

[2] Stambaugh (1999) demonstrates that the use of highly persistent predictive variables may lead to spurious evidence of return predictability.

rate have similar patterns, but the latter is more volatile and takes on more extreme values at peaks and troughs than the former. The correlation coefficient between the two series is 0.63. Furthermore, the figure illustrates two distinct properties of the consumption growth rate as a predictive variable. First, the consumption growth rate has a clear business cycle pattern; it rises during business cycle expansions and reaches its highest values near peaks and falls during business contractions and reaches its lowest values near troughs. For instance, the consumption growth rate drops substantially just after the recession years of the oil shock of 1973-1975. Second, the consumption growth rate has a very low degree of persistence, implying that the consumption growth rate does not suffer from the statistical problems that arise using a highly persistent predictive variable, cf. Stambaugh (1999).

3 Predicting stock returns

Now I turn to testing the ability of consumption growth rates to predict future excess stock returns. This is done by 1-year ahead predictive regressions:

$$r^e_{t+1} = \alpha + \beta G^c_t + e_{t+1}, \tag{1}$$

where r^e_{t+1} is the 1-year ahead log excess stock return and G^c_t is the consumption growth rate. Table 2 reports OLS estimates, Newey and West (1987) corrected t-statistics, and $\bar{R}^2$-statistics. Significant estimates at the five percent level are in bold. The upper panel of table 2 reports the results for annual consumption growth rates measured as year to year growth rates in quarterly consumption. When the annual consumption growth rate is based upon fourth quarter data, it tracks a substantial amount of the variation in future excess stock returns. The $\bar{R}^2$-statistic is 12.01%, and the slope estimate is significantly negative such that low consumption growth rates predict high future excess stock returns, i.e. expected returns are high at business cycle troughs and low at business cycle peaks. When the annual consumption growth rate is measured based upon other quarters, it loses predictive power; both the t-statistic and the $\bar{R}^2$-statistic fall. The lower panel of table 2 reports the results for quarterly consumption growth rates. Here the evidence is even more striking. The fourth quarter consumption growth rate produces an $\bar{R}^2$-statistic of 18.89%, and the slope estimate is strongly significant (t-statistic of -5.75). When the quarterly consumption growth rate is measured based upon the first, second, and third quarters, the slope estimates are borderline significant or insignificant, and the $\bar{R}^2$-statistics are negligible. These dramatic results relate to the findings of Jagannathan and Wang (2007). They emphasize that the use of fourth quarter data mitigates the effect of measurement error in consumption data as well as the effect of infrequent adjustment of consumption plans that may disrupt the linkage between the consumption growth rate and expected returns.

The above evidence implies that both the 4Q-4Q and 3Q-4Q consumption growth rates have predictive power for future excess stock returns. The 4Q-4Q (annual) consumption growth rate is the sum of the 4Q-3Q (first three quarters) and the 3Q-4Q (fourth quarter) consumption growth rates. To examine whether the 4Q-3Q consumption growth rate also predicts future excess stock returns, I regress the 1-year ahead calendar year excess stock return on the 4Q-3Q consumption growth rate. The slope estimate is -3.24, the Newey-West corrected t-statistic is -1.66, and the $\bar{R}^2$-statistic is 3.31. Hence, the consumption growth rate of the first three quarters does not contain much predictive power for future excess stock returns, implying that the predictive power of the consumption growth rate is related to the fourth quarter.

3.1 Controlling for benchmark predictive variables

To control for benchmark predictive variables, I run predictive regressions of the form:

$$r^e_{t+1} = \alpha + \beta G^c_t + \Phi' Z_t + e_{t+1}, \tag{2}$$

where Z_t is a vector of benchmark predictive variables and G^c_t is the fourth quarter consumption growth rate. I compare the performance of G^c_t with traditional financial predictive variables (dp_t, $TERM_t$, and DEF_t) and the most prominent macro predictive variable ($\widehat{cay}_t$). The benchmark predictive variables are measured on an annual frequency. Table 3 shows that G^c_t contains substantial additional information about future excess stock returns relative to the traditional financial predictive variables. dp_t has a significant slope estimate and explains 6.86% of the variation in 1-year ahead excess stock returns, whereas $TERM_t$ and DEF_t are not able to predict excess stock returns in the post-war period from 1947 to 2005; their slope estimates are insignificant, and the $\bar{R}^2$-statistics are close to zero or negative. When G^c_t is included in the predictive regression with dp_t, the $\bar{R}^2$-statistic increases to 22.34%, and the slope estimate turns out to be insignificant for dp_t. Table 3 shows that G^c_t is also robust to the inclusion of $\widehat{cay}_t$. $\widehat{cay}_t$ has a significant slope estimate, and it produces an $\bar{R}^2$-statistic of 17.48% as a sole predictive variable. By including G^c_t along with $\widehat{cay}_t$, the $\bar{R}^2$-statistic increases to 29.57% and both predictive variables remain significant. To confirm the robustness, I run a predictive regression that includes all the predictive variables; G^c_t, dp_t, $TERM_t$, DEF_t and $\widehat{cay}_t$. The financial predictive variables (dp_t, $TERM_t$ and DEF_t) are all insignificant, and the $\bar{R}^2$-statistic does not increase once these variables are included. Hence, the relevant information about future excess stock returns is contained in G^c_t and $\widehat{cay}_t$; macro predictive variables that provide a direct linkage between time-varying expected returns and the business cycle.

As a further robustness check, I examine the predictive power of the benchmark predictive variables measured based upon fourth quarter data. Table 4 shows that the predictive power of dp_t and $\widehat{cay}_t$ does not change much when they are measured based upon fourth quarter data instead of annual data.[3] dp_t produces an $\bar{R}^2$-statistic of 7.89% on fourth quarter data compared to 6.86% on annual data, whereas $\widehat{cay}_t$ produces an $\bar{R}^2$-statistic of 13.75% on fourth quarter data compared to 17.48% on annual data.[4] Both

[3] I only report results for dp_t and $\widehat{cay}_t$ since both $TERM_t$ and DEF_t produce the same results with fourth quarter data as they do with annual data.

[4] For $\widehat{cay}_t$ the fourth quarter data starts in 1951, while the annual data starts in 1948.

dp_t and $\widehat{cay}_t$ continue to be significant as sole predictive variables, but turn insignificant when G^c_t is included to the predictive regression. Overall, the evidence suggests that the fourth quarter effect is a pure consumption effect.

3.2 Small sample bias

This section deals with small sample bias in the predictive regression (1). Specifying the predictive variable (x_t) as a stationary first-order autoregressive process, Stambaugh (1999) sets up the following model:

$$r^e_{t+1} = \alpha + \beta x_t + e_{t+1}, \qquad e_{t+1} \sim niid\left(0, \sigma^2_e\right) \tag{3}$$
$$x_{t+1} = \delta + \rho x_t + u_{t+1}, \qquad u_{t+1} \sim niid\left(0, \sigma^2_u\right) \tag{4}$$

and derives the small sample bias in β as a function of the degree of persistence in x_t and the correlation between the innovations in (3) and (4). Stambaugh (1999) shows that the small sample bias is particularly severe for financial predictive variables such as the dividend-price ratio since it is highly persistent, and its innovations are highly correlated with the innovations in returns. The small sample bias is less relevant with the fourth quarter consumption growth rate as predictive variable for two reasons. First, the fourth quarter consumption growth rate is not highly persistent. It has an AR(1) coefficient of -0.05, whereas the dividend-price ratio has an AR(1) coefficient of 0.95. Second, since the fourth quarter consumption growth rate is a pure macroeconomic variable, its innovations have relatively low correlation with the innovations in returns. The correlation between the innovations in the fourth quarter consumption growth rate and the innovations in the excess stock return is 0.27, whereas the correlation between the innovations in the dividend-price ratio and the innovations in the excess stock return is -0.61. To confirm that small sample bias is not an issue, I apply the following bootstrap procedure:

First, I estimate the following model, where G^c_t is the fourth quarter consumption growth rate:

$$r^e_{t+1} = \alpha + e_{t+1}, \tag{5}$$
$$G^c_{t+1} = \delta + \rho G^c_t + u_{t+1}. \tag{6}$$

Following the common practice (Nelson and Kim 1993, Goetzmann and Jorion 1993, and Kothari and Shanken 1997), I bootstrap under the null of no predictability by imposing the constraint that $\beta = 0$ and assume that the predictive variable follows an AR(1) model.[5] Second, I construct $100,000$ bootstrap samples of length $T + 1,000$ by randomly selecting residual pairs from (5) and (6). I use the OLS estimates of α, δ, and ρ, and set the initial values of r^e_t and G^c_t equal to their sample averages. The first $1,000$ observations are thrown away to avoid any effects from using the sample averages as starting values. Third, I estimate β from each bootstrap sample using equation (1) and then calculate a

[5] I have also used an AR(2) model as the data generating process for G^c_t. The AR(2) coefficient is -0.32. Using an AR(2) model produces nearly identical results as the AR(1) model.

95% bootstrap confidence interval for β using the lower 2.5th percentile and the upper 97.5th percentile of the $100,000$ bootstrap samples.

The average value of the $100,000$ artificial slope coefficients simulated under the null of no predictability is -0.03, and the 95% bootstrap confidence interval is $[-1.94; 1.90]$. Since the confidence interval does not include the OLS estimate $\hat{\beta} = -3.19$ (reported in table 2), the bootstrap analysis confirms the conclusion that the fourth quarter consumption growth ratio predicts future excess stock returns.

4 Conclusion

This paper shows that the consumption growth rate based upon fourth quarter data tracks predictable variation in future excess stock returns. When the consumption growth rate is measured based upon other quarters, it loses predictive power. This is consistent with Jagannathan and Wang (2007) who emphasize that the use of fourth quarter data mitigates the effect of measurement error in consumption data as well as the effect of infrequent adjustment of consumption plans that may disrupt the linkage between the consumption growth rate and expected returns.

The fourth quarter consumption growth rate is a pure macroeconomic variable and provides a direct linkage between time-varying expected returns and the business cycles; it predicts high excess stock returns at business cycle troughs and low excess stock returns at business cycle peaks. The fourth quarter consumption growth rate outperforms financial predictive variables such as the dividend-price ratio, the term spread, and the default spread. The fourth quarter consumption growth rate also provides statistically significant additional information about future excess stock returns beyond that contained in the consumption-wealth ratio. Importantly, the fourth quarter consumption growth rate is an almost i.i.d. process, which eliminates potential concerns about finding spurious evidence of return predictability, cf. Stambaugh (1999).

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Table 1. Consumption growth: summary statistics (in %)

	Annual consumption growth			
	1Q-1Q	2Q-2Q	3Q-3Q	4Q-4Q
Mean	2.29	2.28	2.29	2.33
SD	1.42	1.34	1.37	1.42
Min	−0.36	−0.31	−1.08	−0.78
Max	5.72	5.40	4.83	5.70
Range	6.08	5.71	5.91	6.48
	Quarterly consumption growth			
	4Q-1Q	1Q-2Q	2Q-3Q	3Q-4Q
Mean	2.22	2.43	2.24	2.33
SD	2.10	1.99	2.10	2.32
Min	−4.17	−4.62	−3.88	−4.93
Max	6.76	6.79	5.65	9.52
Range	10.92	11.40	9.52	14.45

Notes. The table reports summary statistics of consumption growth rates. In the upper panel, the consumption growth rate is measured annually as year to year growth rates in quarterly consumption, i.e. 4Q-4Q is the consumption growth rate calculated from the fourth quarter in year $t-1$ to the fourth quarter in year t. In the lower panel, the consumption growth rate is measured quarterly, i.e. 3Q-4Q is the fourth quarter consumption growth rate calculated from the third quarter in year t to the fourth quarter in year t. The quarterly consumption growth rates are scaled by 4 such that the unit of measurement is percentage points per year.

Table 2. Predicting excess stock returns with G_t^c.

	Annual consumption growth					
	Constant	1Q-1Q	2Q-2Q	3Q-3Q	4Q-4Q	$\bar{R}^2(\%)$
Estimate	**0.12**	**−2.86**				5.30
t-value	4.27	−2.71				
Estimate	**0.14**		**−3.76**			8.16
t-value	4.17		−2.72			
Estimate	**0.13**			−2.99		3.20
t-value	3.32			−1.76		
Estimate	**0.16**				**−4.26**	12.01
t-value	4.18				−3.24	
	Quarterly consumption growth					
	Constant	4Q-1Q	1Q-2Q	2Q-3Q	3Q-4Q	$\bar{R}^2(\%)$
Estimate	**0.07**	−0.69				−0.91
t-value	2.96	−0.90				
Estimate	**0.09**		**−1.33**			0.93
t-value	3.47		−2.07			
Estimate	**0.08**			−1.13		−0.14
t-value	3.35			−1.61		
Estimate	**0.13**				**−3.19**	18.89
t-value	5.92				−5.75	

Notes. This table reports results of predictive regressions for the 1-year ahead log excess return (r_{t+1}^e) on the lagged consumption growth rate (G_t^c): $r_{t+1}^e = \alpha + \beta G_t^c + e_{t+1}$. For each regression, the table reports OLS estimates, Newey-West corrected t-statistics, and $\bar{R}^2$-statistics. Significant estimates at the five percent level are in bold. In the upper panel, the consumption growth rate is measured annually as year to year growth rates in quarterly consumption, i.e. 4Q-4Q is the consumption growth rate calculated from the fourth quarter in year $t-1$ to the fourth quarter in year t. In the lower panel, the consumption growth rate is measured quarterly, i.e. 3Q-4Q is the fourth quarter consumption growth rate calculated from the third quarter in year t to the fourth quarter in year t. For 1Q-1Q and 4Q-1Q consumption growth rates, the 1-year ahead excess stock return is measured from April to the next March. For 2Q-2Q and 1Q-2Q consumption growth rates, the 1-year ahead excess stock return is measured from July to the next June. For 3Q-3Q and 2Q-3Q consumption growth rates, the 1-year ahead excess stock return is measured from October to the next September. For 4Q-4Q and 3Q-4Q consumption growth rates, the 1-year ahead excess stock return is measured over the calendar year.

Table 3. Controlling for alternative predictive variables.

	Constant	G_t^c	dp_t	$TERM_t$	DEF_t	$\widehat{cay}_t$	$\bar{R}^2(\%)$
Estimate	**0.45**		**0.11**				6.86
t-value	2.71		2.23				
Estimate	**0.42**	**−2.92**	0.09				22.34
t-value	2.77	−4.90	1.80				
Estimate	0.04			1.71			0.65
t-value	1.33			1.57			
Estimate	**0.11**	**−3.18**		1.70			19.85
t-value	3.57	−5.74		1.50			
Estimate	0.04				1.97		−1.54
t-value	0.77				0.45		
Estimate	**0.13**	**−3.19**			−0.00		17.38
t-value	2.60	−5.51			−0.00		
Estimate	**−0.92**					**4.07**	17.48
t-value	−3.56					3.86	
Estimate	**−0.67**	**−2.63**				**3.29**	29.57
t-value	−2.36	−4.55				2.88	
Estimate	−0.20	**−2.60**	0.07	1.40	−2.66	**2.43**	28.75
t-value	−0.51	−4.24	1.43	1.23	−0.83	2.04	

Notes. This table reports results of predictive regressions for the 1-year ahead log excess return (r_{t+1}^e) on lagged predictive variables: $r_{t+1}^e = \alpha + \beta G_t^c + \Phi' Z_t + e_{t+1}$. G_t^c is the fourth quarter consumption growth rate and Z_t is a vector of benchmark predictive variables. For each regression, the table reports OLS estimates, Newey-West corrected t-statistics, and $\bar{R}^2$-statistics. Significant estimates at the five percent level are in bold.

Table 4. Controlling for alternative predictive variables based on fourth quarter data.

	Constant	G_t^c	dp_t	$\widehat{cay}_t$	$\bar{R}^2(\%)$
Estimate	**0.57**		**0.11**		7.89
t-value	2.84		2.42		
Estimate	**0.50**	**−2.86**	0.08		22.45
t-value	2.62	−4.67	1.85		
Estimate	**0.05**			**5.37**	13.75
t-value	2.82			2.86	
Estimate	**0.12**	**−2.95**		3.89	26.44
t-value	3.97	−3.94		1.94	
Estimate	0.39	**−2.90**	0.06	3.42	26.96
t-value	1.67	−4.27	1.13	1.64	

Notes. This table reports results of predictive regressions for the 1-year ahead log excess return (r_{t+1}^e) on lagged predictive variables: $r_{t+1}^e = \alpha + \beta G_t^c + \Phi' Z_t + e_{t+1}$. G_t^c is the fourth quarter consumption growth rate and Z_t is a vector of benchmark predictive variables measured based upon fourth quarter data. For each regression, the table reports OLS estimates, Newey-West corrected t-statistics, and $\bar{R}^2$-statistics. Significant estimates at the five percent level are in bold.

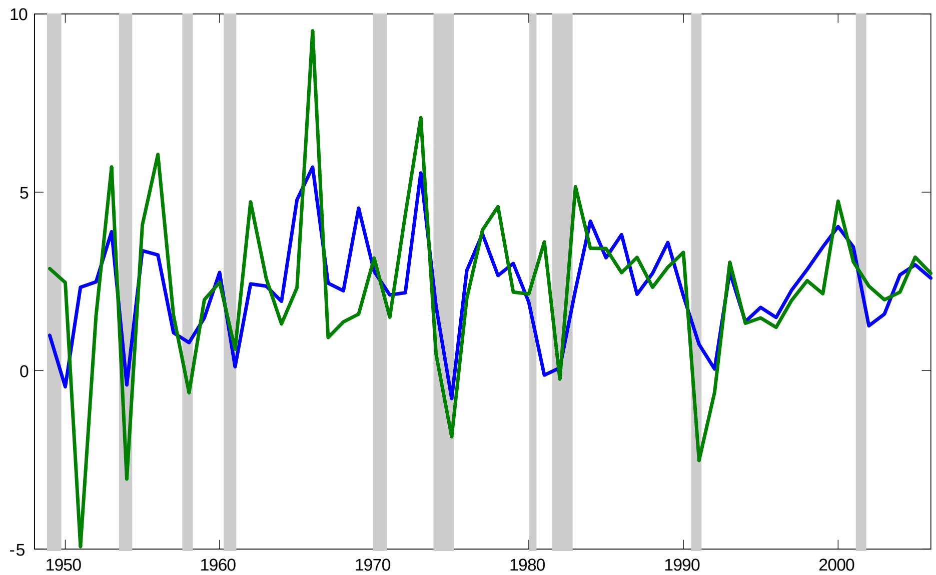

Fig. 1. The consumption growth rate.

The figure plots the annual 4Q-4Q consumption growth rate (blue line) and the quarterly 3Q-4Q consumption growth rate (green line). The quarterly 3Q-4Q consumption growth rate is scaled by 4 such that the unit of measurement is percentage points per year.

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