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The Role of the Discount Rate in Investment and Employment Decisions

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Abstract

Time variation in the discount rate affects investment and employment decisions in a manner consistent with *Q*-theory predictions. This evidence is uncovered when using cyclical consumption as a proxy for the discount rate. The results, which are consistent across both U.S. and international data, suggest that firms respond rationally to variations in the cost of capital and that the discount rate has a substantial impact on macroeconomic dynamics and hence business cycle fluctuations.

I. Introduction

Lettau and Ludvigson (2002) derive the theoretical result that the discount rate should have implications not only for investment today, but also for future investment at long horizons. Similarly, Chen and Zhang (2011) derive a dynamic model that relates the discount rate to both short- and long-term employment growth. However, while both of these models provide novel and interesting insights, the empirical evidence to support them is still limited. For instance, until now, no single proxy for the discount rate has been shown to predict both investment and employment in a way that is consistent with *Q*-theory models. In addition, no international evidence exists to support the theoretical result that discount rate variation should explain long-term fluctuations in both investment and employment.

Our contribution is to show that both investment and employment growth are predictable by the discount rate in a manner that is consistent with *Q*-theory models. We uncover strong and robust evidence, using U.S. and international data, that managers do adjust investment and employment in the long run, in line with the novel predictions in Lettau and Ludvigson (2002) and Chen and Zhang (2011). As a result, we are able to show that time variation in the discount rate as measured by the equity market risk premium matters for macroeconomic dynamics. The crux to uncovering these findings is the ability to accurately measure

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discount rate variation over the business cycle through employing a robust predictor of stock returns.

Research on stock return predictability, which is the main source for understanding if discount rates vary, has produced mixed results.[1] However, in a recent article, Atanasov, Møller, and Priestley (2020) derive a new consumption-based predictor variable, cyclical consumption (CC), that is consistent with Campbell and Cochrane's (1999) habit-based model that features time variation in risk aversion. The empirical evidence in Atanasov et al. (2020) shows that there is substantial discount rate variation in both good and bad economic times and over short and long horizons. Consequently, this result opens up the possibility of more accurately testing the production-based model's predictions about the impact of discount rate variation on investment and employment, which in turn may lead to a better understanding of how the discount rate affects business cycle fluctuations, with implications not just for finance but also macroeconomics.

The main result of the article is that the long-run implications of the dynamic investment and employment models of Lettau and Ludvigson (2002) and Chen and Zhang (2011) are confirmed in the data as long as we exploit new insights into how to measure discount rate variation through stock market return predictability. We find that if the discount rate is measured by CC, it contains significant predictive power for stock returns, investment growth, and employment growth, while other proxies for the discount rate often fail to contain significant predictive power or predict with the wrong sign according to the theoretical models. The impact of the discount rate as measured by CC is substantial, both economically and statistically. This evidence suggests that corporate managers respond rationally to variations in their firm's cost of capital when making investment and employment decisions. In turn, the results indicate that discount rate variation can have a major impact on business cycle fluctuations.

We consider a host of robustness tests. First, we provide international evidence from a wide cross section of countries in order to analyze whether the U.S.-based predictability patterns are present outside of the United States. The international results show that investment growth and employment growth are predictable from variation in discount rates in a way that is fully consistent with the U.S. evidence. The international evidence thereby lends further support to the theoretical predictions in Lettau and Ludvigson (2002) and Chen and Zhang (2011). Second, the findings using U.S. data are generally robust to how consumption is measured with the exception that including services weakens the extent of predictability. This finding supports the analysis in Kroencke (2017) who argues that the filtering of services in the construction of the data reduces the link to asset market data. Third, the construction of cyclical consumption is undertaken using a detrending filter proposed in Hamilton (2018). We show that the results regarding investment and employment growth predictability are robust to a wide range of different specifications of the filter. Fourth, investment and employment growth predictability by

[1]Goyal and Welch (2008) show that a long list of predictor variables are inconsistent and poor predictors of stock returns. Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018) find that popular predictor variables can only forecast stock returns in bad times, whereas there is essentially no evidence of predictability in good times (i.e., during business cycle expansions).

cyclical consumption is also robust to using controls for other suggested predictor variables of stock market returns, which are generally unable to predict investment and employment growth, and the inclusion of macroeconomic controls in the predictive regressions.

The rest of the article is organized as follows: Section II presents the dynamic models of investment and employment and their testable predictions. Section III presents the data and motivates why cyclical consumption is an appropriate proxy for capturing time variation in the discount rate. Section IV presents U.S. empirical evidence on predictability of investment and employment growth. Section V presents international evidence. Section VI concludes.

II. Dynamic Models of Investment and Employment

The single period investment model of Tobin (1969) predicts that a decrease (increase) in the discount rate leads to an increase (decrease) in investment. While this effect should happen in the short run, exactly when in the data the effect should be observed is uncertain, because it depends on whether there is time to build or plan. Abel and Blanchard (1986) find that it is the discount rate and not marginal profitability that drives investment. Lamont (2000) finds that investment plans can forecast both aggregate investment and stock returns at short horizons with a lag attributed to time to build/plan. However, Lamont's (2000) evidence of the role between the discount rate and short-term investment is rather indirect.

Equilibrium models with capital adjustment costs have been useful in explaining the equity market premium (see, e.g., Jermann (1998), (2010)) and the value effect (Zhang (2005), Cooper (2006)). In addition, cross-sectional asset-pricing studies have found that returns on individual stocks or portfolios of stocks differ according to their loadings on an investment to asset (capital) factor. The investment factor is derived from a *Q*-theory-based production model and is important in accounting for many stock market anomalies (see, e.g., Hou, Xue, and Zhang (2015), (2020), Hou, Mo, Xue, and Zhang (2021)).

In search models of employment (such as Mortensen and Pissarides (1994)), the risk premium and hence the discount rate are constant, and consequently, there are no implications about the predictability of employment growth by the discount rate. Extensions of search models in a general equilibrium framework that include employment adjustment costs have been shown to be crucial in explaining the equity market premium, macroeconomic quantities, and the presence of rare disasters. For example, Petrosky-Nadeau, Zhang, and Kuehn (2018) use a globally nonlinear algorithm to solve a standard search model of equilibrium unemployment and show that due to adjustment costs in the labor market, rare disasters such as those in Rietz (1988) and Barro (2006) can arise endogenously. Their model captures the dynamics of the unemployment rate and its impact on output. Bai and Zhang (2022) use search models of employment in a general equilibrium framework with rare disasters and show that this model helps explain the equity market risk premium and macroeconomic quantities. They also show that as the discount rate falls, unemployment falls, a result also found in simulations of a partial equilibrium model in Hall (2017).

Given the evidence that both investment and employment dynamics play an important role in equity markets, it is somewhat a puzzle that there appears to be scant empirical evidence of a direct link between the discount rate and future investment and employment. The goal of this article is to investigate empirically how variations in the discount rate affect investment and employment in the long run. Dynamic models of investment and employment that relate these quantities to the discount rate are provided in Lettau and Ludvigson (2002) and Chen and Zhang (2011). Both models outline the direct role that the discount rate can have on future investment and employment decisions. These dynamic models provide a rich set of empirical predictions that we discuss in the following subsections.

A. Investment

Lettau and Ludvigson (2002) derive a novel insight into the role of the discount rate on long-run investment growth, which predicts that a fall (rise) in the discount rate today leads to a fall (rise) in long-run investment. The intuition is as follows: If the discount rate falls today, stock prices rise, the cost of capital declines, and hence, according to Tobin's model, investment should start to rise. Their insight is that going forward, the decrease in the discount rate today leads to future lower stock returns, which eventually will drive down prices in the future. As a result, the cost of capital will start to rise, and consequently, future investment growth will actually fall in the long run. Thus, a fall (rise) in the discount rate today implies a fall (rise) in investment in the long run.

To see the details of how this multiperiod model works, we follow Lettau and Ludvigson (2002) who derive the following expression for the natural logarithm of Tobin's Q, q_t:

$$q_t \approx E_t\left[\sum\nolimits_{j=0}^{\infty}\rho_q^j\left[(1-\rho_q)m_{t+1+j}-r_{it+1+j}+\phi_{t+j}\right]\right], \tag{1}$$

where q_t is expressed as a first-order function of expected marginal profits, m_{t+1+j}, and expected future investment returns, r_{it+1+j}. ϕ_{t+j} contains variance and covariance terms along with linearization constants, and $\rho_q=1/(1+\exp(\overline{m-q}))$. The discount rate is embodied in the investment returns, r_{it+1+j}. It is clear that a fall in future discount rates through r_{it+1+j} increases q_t, and with convex adjustment costs, it follows that investment increases.

Lettau and Ludvigson (2002) then use the Campbell and Shiller (1988) decomposition of stock prices to show that q_t has a common element with p_t:

$$p_t \approx E_t\left[\sum\nolimits_{j=0}^{\infty}\rho_p^j\left[(1-\rho_p)d_{t+1+j}-r_{st+1+j}\right]\right], \tag{2}$$

where p_t is the current stock price, d_{t+1+j} is the expected future dividend, r_{st+1+j} is the future expected stock return, and $\rho_p=1/\left(1+\exp\left(\overline{d-p}\right)\right)$. Comparing equations (1) and (2), it follows that p_t is closely related to q_t, but with the difference that the discount rate is embodied in investment returns in equation (1) and embodied in stock returns in equation (2). Cochrane (1991) shows that aggregate stock returns are equal to aggregate investment returns and provides empirical support for this relation. Liu, Whited, and Zhang (2009) show that investment returns are equal to the firm's weighted average cost of capital and provide evidence that stock returns are equal to levered investment returns at the portfolio level. Therefore, given that $r_{st+1+j} = r_{it+1+j}$, we are able to assert that both p_t and q_t depend on expected stock returns.

To see how observable predictor variables have been related to expected returns, note that from the stock return predictability literature, the Campbell and Shiller decomposition is written as:

$$d_t - p_t \approx E_t\left[\sum\nolimits_{j=0}^{\infty} \rho_p^j \left[r_{st+1+j} - \Delta d_{t+1+j}\right]\right], \tag{3}$$

and the dividend–price ratio $\mathrm{DP}_t \equiv d_t - p_t$ is shown to predict long-horizon returns.

Lettau and Ludvigson (2002) note that the Q-theory implies the following for expected investment returns:

$$E_t r_{it+1} \approx \rho_q E_t \Delta q_t + \left(1 - \rho_q\right) E_t[m_{t+1} - q_t] + \phi_t, \tag{4}$$

and given that $r_{st+1+j} = r_{it+1+j}$, we can substitute equation (4) into (3):

$$d_t - p_t \approx E_t\left[\sum\nolimits_{j=0}^{\infty} \rho_p^j \left[\rho_q \Delta q_{t+1+j} + (1-\rho_q)\left[m_{t+1+j} - q_{t+j}\right] + \phi_{t+j} - \Delta d_{t+1+j}\right]\right]. \tag{5}$$

Now, from equations (3) and (5), it is clear that a variable that forecasts long-horizon stock returns, such as DP_t in equation (3), can also be used to forecast long-horizon variation in Δq_t. Given that we can think of investment as being an increasing function of q_t, the testable implication is that DP_t should forecast investment growth over the long horizon. Lettau and Ludvigson (2002) outline the relation between predictor variables that proxy discount rate variations and investment growth. First, from equation (3), a decrease in DP_t predicts a decrease in expected returns (discount rates). From equation (5), a decrease in the discount rate leads to a fall in the growth rate in q_t and therefore investments over long horizons. That is, future investment growth should have a positive correlation with expected returns, which is the opposite of the 1-period Q model where a decline in the discount rate leads to a contemporaneous increase in investment. The ability to predict investment grows with the horizon because of the infinite discounted sum of Δq_{t+1+j} on the right-hand side of equation (5). To summarize, a fall in the discount rate today should predict a short-run increase in investment, according to Tobin's model, but then a subsequent fall in investment in the long run according to Lettau and Ludvigson (2002) model. Of course, the opposite happens when the discount rate increases.

In principle, any variable that predicts stock returns should work in predicting q and hence investment. Lettau and Ludvigson (2002) derive a similar version of equation (5) using CAY on the left-hand side and find evidence that is consistent with discount rate proxies predicting long-run investment growth.

We test the hypothesis of predictable investment growth from discount rate variation by using a predictive regression of the form:

$$\Delta i_{t+h} = i_{t+h} - i_t = \alpha + \beta Z_t + \varepsilon_{t+h}, \tag{6}$$

where $\Delta i_{t+h} = i_{t+h} - i_t$ is h-period ahead logarithm growth in investment, Z_t is a discount rate proxy, and ε_{t+h} is the error term.

B. Employment

Chen and Zhang (2011) derive a novel dynamic model of employment growth. The intuition underlying their insight is the same as that of Lettau and Ludvigson (2002) in that a fall in the discount rate at the beginning of period t, which is accompanied by a rise in stock prices, leads to an increase in the marginal benefit of hiring and hence should increase actual hiring. With a 1-period lag in planning, the employment stock increases at the beginning of period $t+1$, implying that a discount rate drop today will lead to a short-run increase in employment growth. The increase in stock price and fall in the discount rate at the beginning of period t imply that returns will fall on average during period t, which means that the stock price will drop at the beginning of period $t+1$, and so will the level of hiring. Time-to-build effects again imply that the actual employment stock will drop only at the beginning of period $t+2$. Based on this, a change in the discount rate today should forecast a short-run change in employment with a negative slope and a long-run change in employment with a positive slope.

To see this in detail, we follow Chen and Zhang (2011) who base their testable hypotheses about predictable employment growth on the work of Yashiv (2000) and Merz and Yashiv (2007) that brings search and matching models of employment into an expression for firm value. The first step here is to define the adjustment costs of hiring as quadratic:

$$\left(\frac{a}{2}\right)\left(\frac{\lambda_t J_t}{N_t}\right)^2 N_t, \tag{7}$$

where $a>0$, N_t is the total employment, J_t represents job vacancies, and λ_t is the probability that a vacancy will be filled. Given separation rates, s, happen at a constant rate between 0 and 1, the stock of employment evolves according to

$$N_{t+1} = (1-s)N_t + \lambda_t J_t. \tag{8}$$

This relation is important since it embodies a 1-period time-to-build since hiring at time $t, \lambda_t J_t$, only delivers new productive workers at time $t+1$.

Hiring costs are rising and convex in the number of hires and falling in the stock of workers. The motivation for this specification is that the costs of searching and screening for new workers and training them increase with the numbers that need hiring.

Assuming that the firm decides on the number of workers in order to maximize the discounted present value of future cash flows, the return to hiring is given as the ratio of the marginal benefit of hiring to the marginal cost of hiring:

$$R^H_{t+1} = \frac{f(X_{t+1}) - W_{t+1} + \left(\frac{a}{2}\right)\left(\frac{N_{t+2}}{N_{t+1}}\right)^2 - \left(\frac{a}{2}\right)(1-s)^2}{a\left(\frac{N_{t+1}}{N_t}\right) - a(1-s)}, \tag{9}$$

where X_t is a productivity shock and W_t is the wage rate. Cochrane (1991) shows that with constant returns, to scale the return from hiring is equivalent to the stock market return (see also Liu et al. (2009)). So, replacing R^H_{t+1} with the stock market return, which embodies the discount rate, provides a number of testable hypotheses about employment growth and discount rates (expected stock returns) that are the same as those regarding investment growth and discount rates. In particular, an increase in the discount rate at time t should forecast initially lower employment growth $\left(\frac{N_{t+1}}{N_t}\right)$ and subsequently higher employment growth $\left(\frac{N_{t+2}}{N_{t+1}}\right)$.

We can test the basic idea of whether the discount rate predicts future employment growth with the following regression:

$$\Delta e_{t+h} = e_{t+h} - e_t = \alpha + \beta Z_t + \varepsilon_{t+h}, \tag{10}$$

where $\Delta e_{t+h} = e_{t+h} - e_t$ is h-period ahead logarithm growth in employment, Z_t is a discount rate proxy, and ε_{t+h} is the error term.

III. Data

Data on investment are private nonresidential investments (seasonally adjusted and inflation adjusted) available from the Bureau of Economic Analysis. Data on employment are private nonfarm payrolls that exclude government employees (seasonally adjusted) available from the Bureau of Labor Statistics. We calculate the growth rate of the natural logarithm of investment and employment.

Following the findings in Atanasov et al. (2020), as the proxy to track movements in the discount rate, we extract cyclical consumption fluctuations using aggregate seasonally adjusted consumption expenditures on nondurables from the National Income and Product Accounts Table 7.1, available from the Bureau of Economic Analysis.[2] The data are quarterly, in real per capita terms, and measured in 2012 chain weighted dollars. We use the simple and robust detrending method of Hamilton (2018) to extract the cyclical component of consumption. Following Hamilton's linear projection procedure, we regress the logarithm of real per capita consumption, c_t, on a constant and 4 lagged values of consumption as of date $t-k$:

$$c_t = b_0 + b_1 c_{t-k} + b_2 c_{t-k-1} + b_3 c_{t-k-2} + b_4 c_{t-k-3} + \omega_t, \tag{11}$$

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

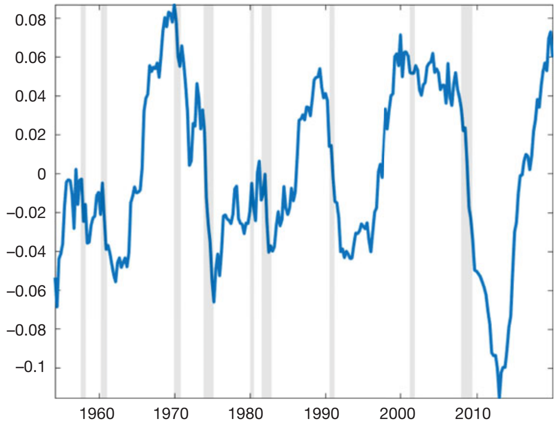
$$\mathrm{CC}_t = c_t - \widehat{b}_0 - \widehat{b}_1 c_{t-k} - \widehat{b}_2 c_{t-k-1} - \widehat{b}_3 c_{t-k-2} - \widehat{b}_4 c_{t-k-3}. \tag{12}$$

Since CC_t is computed based on a 1-sided filter, any finding that it predicts the future values of another variable should represent true predictive ability rather than an artifact of the way consumption is detrended. In addition, this detrending procedure ensures that the cyclical component is stationary and consistently estimated for a wide range of nonstationary processes (Hamilton, 2018).

[2]We use nondurable consumption because several studies argue that services are more plagued by measurement errors than nondurable goods (see, e.g., Wilcox (1992), Savov (2011), Kroencke (2017)). Kroencke (2017) argues that the filtering of services in the construction of the data reduces the link to asset market data. We perform robustness tests using different definitions of aggregate consumption data.

FIGURE 1

Cyclical Consumption



Calculating the cyclical component of consumption using the Hamilton procedure requires a choice of k in equation (11). With the purpose of capturing a slowly time-varying risk premium and hence the discount rate, Atanasov et al. (2020) show that a horizon around 6 years in the detrending filter is consistent with implications of the Campbell and Cochrane (1999) external habit formation model. We estimate equation (11) over the period 1947:Q1 to 2019:Q4 and then compute CC_t using equation (12) with $k = 24$ quarters, implying that the first observation on CC_t is for 1953:Q4 and the last is for 2019:Q4.

Figure 1 shows a time-series plot of CC computed from equation (12) for $k = 24$ quarters along with recession dates as defined by the NBER. The figure illustrates that CC has a clear pro-cyclical pattern. It increases during economic expansions and tends to reach its highest values just prior to the outbreak of recessions and decreases during economic contractions and tends to reach its lowest values near the bottom of recessions. Atanasov et al. (2020) show that these fluctuations in cyclical consumption constitute a more accurate description of good and bad economic times than previously employed predictor variables, and CC is the most successful predictor of stock returns and hence contains relevant information about future discount rates.

As a control, we consider popular predictors of aggregate stock returns, which have been used previously to predict investment growth and employment growth in Lettau and Ludvigson (2002) and Chen and Zhang (2011). These are the dividend–price ratio (DP), which is the logarithm of a 12-month moving sum of dividends paid on the S&P 500 index minus the logarithm of prices on the S&P 500 index; the term spread (TMS), which is the long-term yield on government bonds minus the 3-month treasury bill rate; the default yield spread (DFY), which is the difference between BAA- and AAA-rated corporate bond yields; the 3-month treasury bill rate (TBL); and the consumption–wealth ratio (CAY), which is the residual from a cointegrating relation between the logarithm of consumption, the logarithm of asset (nonhuman) wealth, and the logarithm of labor income (Lettau and Ludvigson (2001)). Data on these variables are available from the Goyal and Welch (2008) data set.

There are also 4 traditional predictive variables of investment growth that are not related to the discount rate, also used by Lettau and Ludvigson (2002) and Chen and Zhang (2011). These are lagged investment growth (DI) or lagged employment growth (DE), corporate profit growth (DPROFIT) given as the logarithm growth rate in after-tax profits, the q-ratio computed as the market value of equities divided by the net worth, and the real GDP logarithm growth rate (DGDP). Data on these variables are available from the FRED database of the St. Louis Federal Reserve Bank.

Predicting Stock Returns

Which variables are good proxies for the discount rate? To answer this question, we need to assess which variables are able to predict stocks returns. We consider a standard predictive regression model for analyzing aggregate stock return predictability:

$$r_{t+h} = \alpha + \beta Z_t + \varepsilon_{t+h}, \tag{13}$$

where Z_t is a 1-quarter lagged predictor variable, and r_{t+h} is the h-quarter ahead excess return on the aggregate stock market. We measure r_{t+h} as the h-quarter continuously compounded logarithm return on the S&P500 index less the corresponding h-quarter continuously compounded logarithm Treasury bill return. To test the significance of β, we use heteroscedasticity and autocorrelation robust t-statistics of Newey and West (1987) with h lags.

Table 1 provides the results from univariate regressions given in equation (13). It is clear that CC predicts returns at all horizons with a negative coefficient

TABLE 1

Predicting Discount Rates

Table 1 presents the results of predictive regressions, $r_{t+h} = \alpha + \beta Z_t + \varepsilon_{t+h}$, where r_{t+h} is the h-quarter ahead logarithm excess stock market return and Z_t is a predictive variable. The table shows results for the following predictive variables: cyclical consumption (CC), the dividend–price ratio (DP), the term spread (TMS), the default spread (DFY), the short treasury bill rate (TBL), and the consumption–wealth ratio (CAY). For each regression, the table reports the slope estimate, the Newey–West corrected t-statistic (h lags), and the adjusted R^2 statistic. The regressions are estimated over the period 1953:Q4 to 2019:Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
CC	−0.325	−0.656	−1.323	−2.396	−3.163	−4.168	−4.916
t-Stat	−3.072	−3.642	−4.034	−4.201	−4.730	−5.932	−6.911
$\bar{R}^2$	0.029	0.057	0.119	0.215	0.288	0.409	0.443
DP	0.020	0.043	0.080	0.127	0.146	0.168	0.229
t-Stat	1.519	1.734	1.710	1.460	1.297	1.358	1.821
$\bar{R}^2$	0.006	0.017	0.033	0.047	0.046	0.050	0.073
TMS	0.579	1.172	2.467	4.402	6.571	8.284	9.331
t-Stat	1.502	1.663	2.239	3.562	4.608	3.818	2.777
$\bar{R}^2$	0.007	0.016	0.041	0.075	0.131	0.171	0.168
DFY	0.618	2.011	3.347	4.378	5.593	9.821	17.212
t-Stat	0.403	0.843	0.948	0.939	0.951	1.326	1.994
$\bar{R}^2$	−0.003	0.002	0.004	0.004	0.005	0.020	0.052
TBL	−0.312	−0.557	−0.914	−1.320	−1.707	−1.943	−1.953
t-Stat	−1.905	−1.783	−1.756	−2.040	−1.735	−1.336	−0.961
$\bar{R}^2$	0.011	0.018	0.026	0.031	0.039	0.041	0.030
CAY	0.448	0.925	1.720	2.907	3.924	4.995	5.935
t-Stat	2.164	2.412	2.427	2.482	2.622	2.884	3.026
$\bar{R}^2$	0.013	0.029	0.052	0.081	0.112	0.145	0.152

indicating that in good times when consumption is above its trend, the discount rate is predicted to fall. In bad times when consumption falls relative to its trend, the discount rate is predicted to rise. The economic impact of CC is large in that a fall in CC by 1 standard deviation below its mean leads to a rise in the expected return of about 6 percentage points at an annual rate. This evidence suggests substantial discount rate variation. The estimate of the coefficient at the 1-quarter horizon is strongly statistically significant and the associated $\overline{R}^2$ is 0.03. Thus, expected returns and therefore the discount rate are low when cyclical consumption is high in good times and high when cyclical consumption is low in bad times. The coefficient estimates are statistically significant at all horizons, and the $\overline{R}^2$ rises to 0.44 at the 20-quarter horizon. These findings confirm those in Atanasov et al. (2020) that CC is a strong predictor of aggregate stock returns and hence a relevant candidate to track discount rate movements.

The remainder of Table 1 reports stock return predictability regressions using the other predictor variables. The dividend–price ratio, the short rate, and the default spread generally struggle to predict stock returns across horizons when looking at the extent of statistical significance and the $\overline{R}^2$. The term spread has more success at least at horizons greater than 4 quarters: An increasing term spread forecasts higher stock returns and hence a higher discount rate. However, the impact in terms of the $\overline{R}^2$ is much lower than that of CC. CAY has predictive power for returns at all horizons, but also at a much lower extent than CC when comparing $\overline{R}^2$s; for example, the $\overline{R}^2$ is roughly twice as big when using CC. From the perspective of these results, there is evidence to suggest that CC is a more reliable proxy for discount rate movements than previously used predictor variables.

IV. Predicting Investment and Employment Growth

Dynamic models of investment and employment state that in the short run, a fall (rise) in the discount rate should predict an increase (decrease) in both investment and employment growth, whereas in the long run, a fall (rise) in the discount rate should predict a decrease (increase) in investment and employment growth. Therefore, when predicting investment and employment growth with the discount rate, we should expect a positive coefficient on CC in the short run, because an increase in CC reflects good economic times with a lower discount rate and hence higher investment and employment. In contrast, theory implies that we should expect to see a negative coefficient estimate when we regress long-horizon investment and employment growth on CC.

Panel A of Table 2 reports the results of investment growth predictability by CC and shows that the estimated coefficients are negative at all horizons. While the coefficient estimates at the 1- and 2-quarter horizons are not statistically significant, the coefficient estimate at the 4-quarter horizon is statistically significant, but CC only has a minor impact with an $\overline{R}^2$ of 0.03. However, at horizons of 8 quarters and longer, the estimated coefficients are highly statistically significant, and the $\overline{R}^2$ ranges from 0.11 at the 8-quarter horizon to 0.22 at the 20-quarter horizon. At these horizons, the negative coefficient estimates indicate that an increase (decrease) in CC, which corresponds to a fall (rise) in the discount rate, predicts investment to fall in the long run, in line with the predictions of the Lettau and Ludvigson (2002)

TABLE 2

Investment Predictability

Panels A and B of Table 2 present the results of univariate predictive regressions, $\Delta i_{t+h} = i_{t+h} - i_t = \alpha + \beta Z_t + \varepsilon_{t+h}$, where Δi_{t+h} is the h-quarter ahead logarithm growth in investments and Z_t is a predictive variable. Panel A shows results using cyclical consumption (CC) as predictive variable, whereas Panel B shows results for the dividend–price ratio (DP), the term spread (TMS), the default spread (DFY), the treasury bill rate (TBL), and the consumption–wealth ratio (CAY). Panel C reports results from multivariate regressions with CC and CAY. Panel D reports results from multivariate regressions with CC, DP, TMS, DFY, and TBL. For each regression, the table reports slope estimates, the Newey–West corrected t-statistics (h lags), and the adjusted R^2 statistic. The regressions are estimated over the period 1953:Q4 to 2019:Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A. Univariate Regressions with CC							
CC	−0.029	−0.086	−0.280	−0.746	−1.072	−1.229	−1.380
t-Stat	−1.012	−1.478	−2.424	−3.063	−2.785	−2.555	−2.653
$\bar{R}^2$	−0.000	0.007	0.033	0.107	0.165	0.192	0.224
Panel B. Univariate Regressions with DP, TMS, DFY, TBL, or CAY							
DP	−0.007	−0.012	−0.013	0.007	0.027	0.037	0.043
t-Stat	−1.593	−1.261	−0.635	0.197	0.621	0.840	0.954
$\bar{R}^2$	0.014	0.013	0.002	−0.003	0.005	0.011	0.014
TMS	0.033	0.194	0.812	2.302	2.818	2.725	2.128
t-Stat	0.302	0.865	1.928	3.482	3.564	2.701	1.887
$\bar{R}^2$	−0.003	0.002	0.028	0.108	0.121	0.099	0.054
DFY	−2.085	−3.380	−4.353	−2.790	−1.023	−1.010	−2.167
t-Stat	−5.419	−4.479	−3.015	−1.083	−0.311	−0.267	−0.540
$\bar{R}^2$	0.185	0.156	0.087	0.012	−0.002	−0.003	0.002
TBL	−0.009	−0.070	−0.275	−0.673	−0.697	−0.578	−0.579
t-Stat	−0.159	−0.580	−1.244	−2.235	−1.975	−1.503	−1.394
$\bar{R}^2$	−0.004	−0.000	0.014	0.043	0.033	0.017	0.015
CAY	0.063	0.172	0.431	0.881	1.112	1.250	1.315
t-Stat	1.038	1.262	1.371	1.536	1.522	1.372	1.201
$\bar{R}^2$	0.001	0.007	0.019	0.037	0.043	0.047	0.046
Panel C. Multivariate Regressions with CC and CAY							
CC	−0.025	−0.076	−0.258	−0.709	−1.032	−1.187	−1.335
t-Stat	−0.855	−1.275	−2.202	−2.907	−2.655	−2.471	−2.642
CAY	0.057	0.153	0.374	0.750	0.944	1.061	1.080
t-Stat	0.904	1.091	1.165	1.310	1.336	1.229	1.024
$\bar{R}^2$	−0.000	0.011	0.046	0.132	0.195	0.225	0.255
Panel D. Multivariate Regressions with CC, DP, TMS, DFY, and TBL							
CC	−0.088	−0.168	−0.305	−0.504	−0.770	−1.007	−1.275
t-Stat	−2.771	−2.649	−2.456	−1.910	−1.696	−1.803	−2.193
DP	−0.011	−0.016	−0.011	0.027	0.037	0.029	0.020
t-Stat	−2.117	−1.576	−0.509	0.638	0.647	0.463	0.319
TMS	0.354	0.681	1.385	2.599	2.913	2.954	2.101
t-Stat	2.845	2.638	2.838	3.158	2.445	1.764	1.160
DFY	−2.765	−4.546	−6.400	−6.199	−5.208	−5.981	−6.636
t-Stat	−7.750	−6.283	−4.796	−2.834	−1.726	−1.609	−1.575
TBL	0.276	0.422	0.452	0.132	0.178	0.507	0.525
t-Stat	3.944	2.944	1.636	0.274	0.252	0.581	0.541
$\bar{R}^2$	0.273	0.241	0.187	0.215	0.246	0.257	0.261

model. As well as having a large impact in terms of explanatory power, the economic impact is also large. For example, a 1-standard-deviation movement in the discount rate, which is 4.4%, leads to a change in investment based on the 8-quarter horizon estimate of 1.6% per annum, which is a substantial amount compared to the mean growth rate of investment of about 4% per annum.

Since CC contains considerable information about future discount rate variation not already contained in popular forecasting variables, such as DP, TMS, DFY, TBL, and CAY (see Table 1), we examine whether CC also explains a larger fraction of the variation in future investment and employment growth than these variables.

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Panel B of Table 2 reports the results of predicting investment growth with the other predictor variables one at a time. We find that the dividend–price ratio cannot predict investment growth over this sample period, mirroring its lack of predictability for stock returns. In this sample period, we also find that CAY and TBL have little predictive power for investment growth. In contrast, TMS predicts investment growth at medium-term horizons with statistically significant coefficients at horizons of 8–16 quarters. Higher values of TMS, which predicts higher stock returns, predict higher investment, although the degree of predictive power is lower than that of CC. Finally, there is evidence that DFY predicts investment growth at short horizons up to 1 year, but it predicts with the wrong sign according to the dynamic investment model.

Next, we consider multivariate regressions to more directly compare the predictive ability of CC with that of the other predictive variables. Panel C of Table 2 reports the results of predicting investment growth with the two consumption-based variables (CC and CAY) in a joint regression. We again find that CC is statistically significant, and it predicts with the right sign at long horizons, while CAY has the right sign but remains statistically insignificant. Panel D compares CC against the financial predictive variables. We find that CC loses some of its statistical significance at medium-term horizons, but is the only variable that is significant at the 5-year horizon. In addition, the other predictive variables often have significant predictive power at short- and medium-term horizons of up to 3 years.

Panel A of Table 3 examines employment growth predictability. As in the case of investment growth predictability, we find negative coefficient estimates on CC at all horizons, although the estimates are very small and not statistically significant at the 1- and 2-quarter horizons. There is evidence of predictability at the 4-quarter horizon; however, like in the case of investment growth, the economic impact is not very large. There are statistically significant and economically large longer horizon effects at 8 or more quarters. The $\overline{R}^2$ increases from 0.10 at the 8-quarter horizon to 0.26 at the 20-quarter horizon. The economic effect of a 1-standard-deviation movement in the discount rate is substantial with employment changing in response by 0.4% per annum, which is a quarter of the mean annual growth rate of 1.6%.

Panel B of Table 3 reports the results of predicting employment growth with each of the other predictive variables separately. While the dividend–price ratio has no predictive power for investment growth when used as the sole predictor variable, it has significant predictive power for employment growth at horizons of 4 and 5 years. As in the case of predicting investment growth, CAY and TBL have no significant predictive power for employment growth across horizons. TMS has significant predictive for employment growth at 1- to 4-year horizons and predicts with the right sign. Finally, similar to the case of investment growth, DFY predicts employment growth with significantly negative slopes, but this predictive power does not seem to have any relation to time-varying discount rates given that DFY does not have a significant relation to future stock returns.

Panel C of Table 3 shows that in multivariate predictive regressions of employment growth, CC remains statistically significant at 4th–20th quarter horizons when controlling for CAY, while CAY is statistically insignificant in employment growth regressions joint with CC. Panel D reports the results of predicting

TABLE 3

Employment Predictability

Panels A and B of Table 3 present the results of univariate predictive regressions, $\Delta e_{t+h} = e_{t+h} - e_t = \alpha + \beta Z_t + \varepsilon_{t+h}$, where Δe_{t+h} is the h-quarter ahead logarithm growth in employment and Z_t is a predictive variable. Panel A shows results using cyclical consumption (CC) as predictive variable, whereas Panel B shows results for the dividend–price ratio (DP), the term spread (TMS), the default spread (DFY), the treasury bill rate (TBL), and the consumption–wealth ratio (CAY). Panel C reports results from multivariate regressions with CC and CAY. Panel D reports results from multivariate regressions with CC, DP, TMS, DFY, and TBL. For each regression, the table reports slope estimates, the Newey–West corrected t-statistics (h lags), and the adjusted $\bar{R}^2$ statistic. The regressions are estimated over the period 1953:Q4 to 2019:Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A. Univariate Regressions with CC							
CC	−0.003	−0.020	−0.088	−0.264	−0.411	−0.528	−0.634
t-Stat	−0.292	−1.020	−2.188	−2.980	−2.880	−2.745	−2.732
$\bar{R}^2$	−0.003	0.001	0.026	0.101	0.165	0.213	0.261
Panel B. Univariate Regressions with DP, TMS, DFY, TBL, or CAY							
DP	−0.001	−0.000	0.004	0.019	0.034	0.047	0.061
t-Stat	−0.398	−0.073	0.670	1.559	1.947	2.220	2.639
$\bar{R}^2$	−0.003	−0.004	0.002	0.042	0.090	0.133	0.189
TMS	0.019	0.094	0.331	0.812	0.970	0.853	0.551
t-Stat	0.530	1.193	2.024	2.878	2.707	2.086	1.245
$\bar{R}^2$	−0.002	0.007	0.040	0.101	0.097	0.057	0.017
DFY	−0.537	−0.882	−1.100	−0.566	0.297	0.924	1.134
t-Stat	−3.873	−2.978	−1.725	−0.465	0.186	0.487	0.556
$\bar{R}^2$	0.115	0.090	0.043	0.001	−0.003	0.003	0.005
TBL	0.005	−0.007	−0.052	−0.102	−0.025	0.110	0.229
t-Stat	0.249	−0.166	−0.614	−0.746	−0.151	0.566	1.036
$\bar{R}^2$	−0.003	−0.004	0.001	0.004	−0.004	0.001	0.012
CAY	0.006	0.025	0.077	0.129	0.100	0.042	−0.067
t-Stat	0.285	0.529	0.717	0.690	0.430	0.143	−0.185
$\bar{R}^2$	−0.003	−0.002	0.002	0.003	−0.001	−0.004	−0.003
Panel C. Multivariate Regressions with CC and CAY							
CC	−0.002	−0.019	−0.084	−0.260	−0.410	−0.529	−0.642
t-Stat	−0.247	−0.929	−2.071	−2.880	−2.844	−2.784	−2.851
CAY	0.005	0.020	0.058	0.081	0.033	−0.042	−0.180
t-Stat	0.247	0.416	0.537	0.439	0.144	−0.139	−0.449
$\bar{R}^2$	−0.007	−0.002	0.025	0.100	0.162	0.210	0.263
Panel D. Multivariate Regressions with CC, DP, TMS, DFY, and TBL							
CC	−0.007	−0.016	−0.036	−0.111	−0.239	−0.396	−0.541
t-Stat	−0.708	−0.726	−0.802	−1.314	−1.787	−2.285	−2.776
DP	−0.000	0.001	0.010	0.030	0.037	0.036	0.039
t-Stat	−0.219	0.319	1.537	2.320	1.920	1.488	1.474
TMS	0.136	0.293	0.630	1.195	1.387	1.300	0.955
t-Stat	3.288	3.437	3.953	4.624	3.738	2.642	1.827
DFY	−0.789	−1.379	−2.108	−2.534	−2.314	−2.153	−2.135
t-Stat	−6.376	−5.177	−3.689	−2.410	−1.697	−1.404	−1.441
TBL	0.071	0.109	0.115	0.104	0.219	0.400	0.484
t-Stat	2.687	1.976	1.070	0.577	0.875	1.283	1.362
$\bar{R}^2$	0.178	0.163	0.172	0.268	0.318	0.348	0.392

employment growth with CC and the financial predictor variables. We again find that CC stays statistically significant at long horizons and it predicts with the right sign according to the dynamic models. In this multivariate regression, an increase in TMS leads to an increase in employment growth. DFY also predicts employment growth but with the wrong sign from a discount rate point of view. However, given that DFY does not predict stock returns in this sample and has the wrong sign, the predictability of employment growth is unlikely to stem from a discount rate effect.

The results presented in this section show that other predictor variables that have been used to predict stock returns often fail to predict investment or employment growth. The term spread stands out as an exception given that it has significant predictive power for stock returns as well as for both investment and employment growth. However, its predictive power is generally less pronounced in comparison with CC, especially at long horizons. Overall, the results suggest that employing CC to test the Lettau and Ludvigson (2002) model of investment or the Chen and Zhang (2011) model of employment provides strong support for these models, since CC contains significant predictive power for stock returns, investment growth, and employment growth.

The results show that there is strong support for the long-run implications of the theoretical models of Lettau and Ludvigson (2002) and Chen and Zhang (2011) when using CC as a proxy for the discount rate. However, at short horizons, the coefficient estimates have the wrong sign and, hence, we do not see an immediate or short-run increase (decrease) in investment and employment given a decrease (increase) in the discount rate. Therefore, we cannot establish empirical support for the short-run implications of the investment and employment models. However, this result may be due to measurement error problems. In particular, short-term lags in the investment and hiring process due to various frictions may distort the empirical link between the level of the discount rate and short-run fluctuations in investment and employment (Cochrane (1991), Lamont (2000), Lettau and Ludvigson (2002), Chen and Zhang (2011), and Li, Wang, and Yu (2021)). These frictions imply that the short-term implications of the dynamic investment and employment models may be difficult to test and verify. As such, the long-horizon responses of investment and employment to a change in the discount rate provide a cleaner test of the *Q*-theory.

In summary, using CC to proxy discount rate movements uncovers strong support for the long-run implications of the dynamic models of investment and employment growth. The results imply that time variation in the discount rate has a quantitatively important impact on investment and employment growth.

A. Macroeconomic Controls

There are various macroeconomic variables that are unrelated to the discount rate that have been found to predict both investment and employment growth (see, e.g., Barro (1990), Blanchard, Rhee, and Summers (1993), Lamont (2000), Lettau and Ludvigson (2002), and Chen and Zhang (2011)). Based on this literature, we consider the following macroeconomic variables as potential predictors of investment and employment growth: the first lag of the growth in gross domestic product, DGDP; the first lag of the growth in corporate profits, DPROFIT; the first lag of q; and the first lag of the growth rate in either investment or employment, DI or DE. We aim to establish if the importance of the discount rate in predicting investment and employment growth that we have uncovered so far remains after controlling for these macroeconomic variables.

Panel A of Table 4 reports the results of predicting investment growth with CC and four macroeconomic variables. From the table, we see that in the presence of the macroeconomic controls, CC remains strongly statistically significant in predicting investment growth across horizons. The coefficient estimates and their statistical significance are very similar to that reported in Panel A of Table 2 which includes only CC indicating that the role of CC in predicting investment growth is

TABLE 4

Macroeconomic Controls

Panels A and B of Table 4 present results from predictive regressions of the h-period ahead logarithm growth in investment and employment, respectively. As predictive variables, we use cyclical consumption joint with macroeconomic controls. For each regression, the table reports the slope estimates, the Newey–West corrected t-statistic (h lags), and the adjusted R^2 statistic. The regressions are estimated over the period 1953:Q4 to 2019:Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A. Investment Predictability							
CC	−0.031	−0.093	−0.297	−0.741	−1.029	−1.190	−1.348
t-Stat	−1.684	−2.341	−3.114	−3.082	−2.734	−2.536	−2.619
DI	0.395	0.593	0.496	−0.099	−0.483	−0.541	−0.631
t-Stat	6.734	5.115	2.221	−0.272	−1.189	−1.260	−1.366
DGDP	0.524	1.050	2.249	2.317	1.732	1.451	1.632
t-Stat	3.132	3.151	3.598	2.442	1.598	1.209	1.198
DPROFIT	0.068	0.117	0.164	0.243	0.362	0.283	0.244
t-Stat	3.450	3.209	2.557	2.406	3.345	2.168	1.697
q	0.004	0.007	0.011	0.007	−0.002	−0.008	−0.008
t-Stat	1.930	1.618	0.996	0.258	−0.054	−0.179	−0.160
$\overline{R}^2$	0.405	0.378	0.287	0.179	0.214	0.215	0.243
Panel B. Employment Predictability							
CC	−0.009	−0.030	−0.099	−0.263	−0.398	−0.513	−0.608
t-Stat	−2.039	−2.667	−3.287	−3.388	−3.205	−3.166	−3.237
DE	0.668	1.015	1.090	0.730	0.513	0.645	0.505
t-Stat	7.830	5.603	2.843	1.202	0.859	0.973	0.642
DGDP	0.040	0.166	0.477	0.633	0.610	0.589	0.706
t-Stat	0.676	1.374	2.315	2.208	1.905	1.301	1.424
DPROFIT	0.015	0.028	0.034	0.043	0.056	0.021	0.014
t-Stat	2.159	2.020	1.342	1.118	1.333	0.462	0.371
q	0.000	0.000	−0.001	−0.008	−0.017	−0.026	−0.036
t-Stat	0.639	0.368	−0.271	−0.993	−1.443	−1.916	−2.517
$\overline{R}^2$	0.559	0.469	0.291	0.192	0.229	0.279	0.343

independent of the macroeconomic variables. The first lag of investment growth is statically significant at short horizons indicating that investment growth is persistent. At horizons up to 8 quarters, the coefficient on GDP is statistically significant, and the positive coefficient indicates that an increase in GDP leads to a short-run increase in investment. The coefficient estimates on profit growth are statistically significant with the exception of the 20-quarter horizon, and the positive coefficient indicates that an increase in profit growth leads to an increase in future investment. Interestingly, there is no statistically significant role for q in predicting future investment growth. In spite of the role of some of the macroeconomic variables in predicting investment growth, it does not affect the role of the discount rate in predicting investment growth. Furthermore, the incremental contribution of the macroeconomic variables is relatively small at long horizons of 12 or more quarters. For example, relative to the $\overline{R}^2$s when predicting with CC in Table 2, there is only a small incremental increase in them when predicting with CC and the macroeconomic variables.

Panel B of Table 4 reports the results of predicting employment growth with CC and four macroeconomic variables. As in the case of investment growth in Panel A, we observe that CC remains statistically significant across horizons, and that the coefficient estimates and their statistical significance are very similar to those in Panel A of Table 3 that predict with CC alone. The coefficient estimate on lagged employment growth is large and statistically significant indicating that employment growth is more persistent than investment growth. There is no strong evidence that GDP growth or q has predictive power for employment growth, and profit growth is only able to predict employment growth at very short horizons. Therefore, CC maintains its ability to predict employment growth in the presence of macroeconomic variables.

We can confirm that our findings regarding the role of the discount rate in predicting future investment and employment growth are robust to the inclusion of macroeconomic controls suggesting an important role for the discount rate in firms' investment and employment decisions. The macroeconomic variables add predictive power at short horizons, but relatively little at long horizons in comparison with that of CC.

B. Robustness Tests

In this section, we perform 2 robustness tests that focus on the construction of cyclical consumption. First, we use alternative measures of consumption when calculating cyclical consumption. Second, we consider different specifications of the Hamilton filter in the construction of cyclical consumption.

1. Alternative Consumption Measures

Consumption can be measured in various ways that involve decisions regarding whether services should be included and the use of durables vs. nondurables. Several studies argue that services are more plagued by measurement errors than nondurable goods (see, e.g., Wilcox (1992), Savov (2011), and Kroencke (2017)). In the following, we check whether the predictive ability of cyclical consumption is robust toward alternative measures of consumption. Table 5 shows the results when measuring consumption based on i) our baseline case of nondurable goods (nd); ii) services (serv); iii) durable goods (dur); iv) nondurable goods and services (ndserv); v) nondurable and durable goods (goods); and vi) the sum of nondurable goods, services, and durable goods (total).

The first set of results in Panel A of Table 5 repeats the results already presented using nondurable consumption. The next set of results shows rather limited predictive power of investment growth when measuring consumption based on only services, which could be related to the fact that measurement errors are larger in services than other consumption components. Using consumption measured from durables separately leads to similar $\overline{R}^2$s to those recorded using nondurables. Not surprisingly, we report a lower $\overline{R}^2$ when predicting with CC calculated from nondurables and services where the value falls by around a half, but the coefficient estimate is still statistically significant. Using consumption of goods separately leads to similar $\overline{R}^2$s to those recorded using nondurables.

Panel B of Table 5 repeats the robustness exercise for employment where we find the same results as when predicting investment growth. In particular, consumption based on services only cannot predict employment growth, and including services in other measures of consumption weakens predictability. Overall, for both investment and employment, the results suggest that the predictive ability of cyclical consumption is robust toward using alternative measures of consumption, although the predictability is reduced when combining services with other measures of consumption.

TABLE 5

Alternative Consumption Measures

Panels A and B of Table 5 present results from predictive regressions of the *h*-period ahead logarithm growth in investment and employment, respectively. As predictive variable, we use cyclical consumption extracted using different measures of consumption: i) nondurable goods (nd); ii) services (serv); iii) durable goods (dur); iv) nondurable goods and services (ndserv); v) nondurable and durable goods (goods); and vi) the sum of nondurable goods, services, and durable goods (total). For each regression, the table reports the slope estimate, the Newey–West corrected *t*-statistic (*h* lags), and the adjusted $\bar{R}^2$ statistic. The regressions are estimated over the period 1953:Q4 to 2019:Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A. Investment Predictability							
CC^{nd}	−0.029	−0.086	−0.280	−0.746	−1.072	−1.229	−1.380
t-Stat	−1.012	−1.478	−2.424	−3.063	−2.785	−2.555	−2.653
$\bar{R}^2$	−0.000	0.007	0.033	0.107	0.165	0.192	0.224
CC^{serv}	−0.027	−0.078	−0.223	−0.570	−0.804	−0.833	−0.886
t-Stat	−0.717	−0.975	−1.364	−2.001	−2.146	−1.800	−1.787
$\bar{R}^2$	−0.002	0.002	0.012	0.041	0.062	0.058	0.061
CC^{dur}	0.006	0.003	−0.025	−0.137	−0.270	−0.360	−0.416
t-Stat	0.600	0.144	−0.655	−2.103	−3.153	−3.292	−3.322
$\bar{R}^2$	−0.002	−0.004	−0.000	0.041	0.124	0.196	0.242
CC^{ndser}	−0.031	−0.091	−0.279	−0.711	−0.997	−1.067	−1.167
t-Stat	−0.839	−1.234	−1.985	−2.728	−2.640	−2.207	−2.189
$\bar{R}^2$	−0.001	0.004	0.021	0.067	0.100	0.101	0.112
CC^{goods}	−0.002	−0.022	−0.105	−0.348	−0.579	−0.722	−0.829
t-Stat	−0.131	−0.599	−1.522	−2.723	−3.096	−3.016	−3.074
$\bar{R}^2$	−0.004	−0.002	0.012	0.069	0.147	0.202	0.247
CC^{total}	−0.007	−0.040	−0.166	−0.492	−0.776	−0.915	−1.026
t-Stat	−0.245	−0.735	−1.590	−2.560	−2.889	−2.609	−2.584
$\bar{R}^2$	−0.004	−0.001	0.013	0.060	0.114	0.141	0.164
Panel B. Employment Predictability							
CC^{nd}	−0.003	−0.020	−0.088	−0.264	−0.411	−0.528	−0.634
t-Stat	−0.292	−1.020	−2.188	−2.980	−2.880	−2.745	−2.732
$\bar{R}^2$	−0.003	0.001	0.026	0.101	0.165	0.213	0.261
CC^{serv}	0.016	0.017	−0.007	−0.107	−0.190	−0.235	−0.313
t-Stat	1.092	0.566	−0.107	−1.021	−1.467	−1.438	−1.642
$\bar{R}^2$	0.003	−0.001	−0.004	0.008	0.021	0.026	0.041
CC^{dur}	0.006	0.009	0.005	−0.029	−0.081	−0.125	−0.168
t-Stat	1.834	1.252	0.320	−1.146	−2.570	−3.327	−3.486
$\bar{R}^2$	0.013	0.007	−0.003	0.012	0.074	0.141	0.216
CC^{ndser}	0.010	0.004	−0.044	−0.182	−0.294	−0.371	−0.467
t-Stat	0.759	0.134	−0.833	−1.942	−2.381	−2.242	−2.254
$\bar{R}^2$	−0.001	−0.004	0.001	0.031	0.057	0.072	0.098
CC^{goods}	0.005	0.003	−0.021	−0.106	−0.203	−0.288	−0.367
t-Stat	0.844	0.220	−0.857	−2.263	−3.192	−3.533	−3.550
$\bar{R}^2$	−0.001	−0.004	0.001	0.047	0.122	0.192	0.267
CC^{total}	0.010	0.010	−0.020	−0.122	−0.233	−0.321	−0.413
t-Stat	1.104	0.487	−0.508	−1.686	−2.499	−2.573	−2.547
$\bar{R}^2$	0.002	−0.002	−0.002	0.025	0.068	0.102	0.145

2. The Hamilton Filter

We use the Hamilton (2018) filter as our preferred approach to detrend consumption, because it is a simple 1-sided filter that uses only lagged data. Furthermore, it does not require us to know the nature of the nonstationarity in consumption. Calculating the cyclical component of consumption using the Hamilton procedure requires a choice of the cycle parameter k in equation (11). With the purpose of capturing a slowly time-varying risk premium along the lines of the Campbell–Cochrane habit formation model, Atanasov et al. (2020) show that it is appropriate to specify k at long horizons of several years. In the above, we have focused on $k=6$ years, but Atanasov et al. (2020) show that other values of k also

TABLE 6

Cycle Length

Panels A and B of Table 6 present results from predictive regressions of the *h*-period ahead logarithm growth in investment and employment, respectively. As predictive variable, we use cyclical consumption extracted using different values of the cycle length parameter *k*: 3 years (3y), 4 years (4y), 5 years (5y), 6 years (6y), 7 years (7y), 8 years (8y), 9 years (9y), and 10 years (10y). For each regression, the table reports the slope estimate, the Newey–West corrected *t*-statistic (*h* lags), and the adjusted R^2 statistic. The regressions are estimated over the period 1957:Q4 to 2019:Q4 across all values of *k*.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A. Investment Predictability							
CC^{3y}	0.080	0.106	−0.022	−0.653	−1.325	−1.771	−1.966
t-Stat	1.440	0.952	−0.115	−2.629	−4.264	−4.677	−4.344
$\overline{R}^2$	0.012	0.005	−0.004	0.047	0.147	0.230	0.260
CC^{4y}	0.019	−0.016	−0.198	−0.819	−1.368	−1.721	−1.801
t-Stat	0.443	−0.184	−1.313	−3.571	−4.496	−4.255	−3.568
$\overline{R}^2$	−0.003	−0.004	0.011	0.101	0.207	0.286	0.289
CC^{5y}	−0.012	−0.065	−0.270	−0.810	−1.250	−1.483	−1.569
t-Stat	−0.337	−0.912	−2.054	−3.612	−3.647	−3.180	−2.864
$\overline{R}^2$	−0.003	0.002	0.029	0.121	0.211	0.261	0.270
CC^{6y}	−0.032	−0.086	−0.274	−0.749	−1.109	−1.341	−1.498
t-Stat	−1.076	−1.452	−2.344	−2.987	−2.732	−2.595	−2.637
$\overline{R}^2$	0.000	0.007	0.034	0.113	0.184	0.236	0.273
CC^{7y}	−0.025	−0.078	−0.245	−0.666	−1.018	−1.300	−1.422
t-Stat	−0.905	−1.368	−1.977	−2.323	−2.361	−2.578	−2.719
$\overline{R}^2$	−0.001	0.005	0.028	0.095	0.166	0.239	0.261
CC^{8y}	−0.012	−0.052	−0.206	−0.629	−1.003	−1.218	−1.308
t-Stat	−0.405	−0.795	−1.452	−2.097	−2.514	−2.781	−2.917
$\overline{R}^2$	−0.003	0.000	0.020	0.092	0.174	0.224	0.230
CC^{9y}	−0.011	−0.057	−0.237	−0.687	−1.001	−1.178	−1.231
t-Stat	−0.334	−0.819	−1.582	−2.289	−2.605	−2.913	−3.032
$\overline{R}^2$	−0.003	0.001	0.028	0.111	0.175	0.206	0.200
CC^{10y}	−0.024	−0.080	−0.263	−0.667	−0.933	−1.086	−1.166
t-Stat	−0.705	−1.105	−1.691	−2.181	−2.448	−2.857	−3.027
$\overline{R}^2$	−0.001	0.007	0.036	0.104	0.147	0.170	0.176
Panel B. Employment Predictability							
CC^{3y}	0.049	0.077	0.079	−0.079	−0.298	−0.510	−0.658
t-Stat	2.836	2.144	1.117	−0.611	−1.470	−2.056	−2.474
$\overline{R}^2$	0.056	0.041	0.011	0.002	0.047	0.113	0.160
CC^{4y}	0.024	0.028	−0.006	−0.188	−0.404	−0.592	−0.683
t-Stat	1.776	0.977	−0.108	−1.584	−2.263	−2.639	−2.742
$\overline{R}^2$	0.015	0.004	−0.004	0.038	0.121	0.203	0.229
CC^{5y}	0.007	−0.003	−0.061	−0.251	−0.438	−0.579	−0.679
t-Stat	0.558	−0.124	−1.247	−2.553	−2.843	−2.862	−2.817
$\overline{R}^2$	−0.002	−0.004	0.010	0.088	0.174	0.239	0.280
CC^{6y}	−0.005	−0.022	−0.086	−0.265	−0.429	−0.578	−0.682
t-Stat	−0.519	−1.129	−2.148	−2.931	−2.903	−2.885	−2.806
$\overline{R}^2$	−0.003	0.003	0.028	0.109	0.186	0.265	0.314
CC^{7y}	−0.008	−0.027	−0.088	−0.253	−0.425	−0.576	−0.666
t-Stat	−0.933	−1.463	−2.141	−2.672	−2.864	−2.989	−2.870
$\overline{R}^2$	−0.001	0.006	0.031	0.106	0.196	0.284	0.319
CC^{8y}	−0.004	−0.022	−0.083	−0.256	−0.421	−0.550	−0.640
t-Stat	−0.446	−1.042	−1.804	−2.613	−2.998	−3.101	−2.889
$\overline{R}^2$	−0.003	0.003	0.030	0.118	0.208	0.277	0.306
CC^{9y}	−0.008	−0.029	−0.100	−0.271	−0.418	−0.548	−0.639
t-Stat	−0.751	−1.309	−2.041	−2.710	−2.959	−3.091	−2.816
$\overline{R}^2$	−0.001	0.009	0.045	0.135	0.207	0.270	0.300
CC^{10y}	−0.011	−0.033	−0.103	−0.259	−0.399	−0.534	−0.639
t-Stat	−0.969	−1.449	−2.002	−2.451	−2.678	−2.908	−2.703
$\overline{R}^2$	0.002	0.013	0.048	0.121	0.183	0.250	0.296

lead to stock return predictability. To check the robustness toward the specification of k, Table 6 shows the results from predicting investment growth and employment growth for values of k in the range from 3 to 10 years. The results show that high current consumption relative to past consumption (high CC values) predicts low

TABLE 7
Lag Length Specification

Panels A and B of Table 7 present results from predictive regressions of the h-period ahead logarithm growth in investment and employment, respectively. As predictive variable, we use cyclical consumption extracted using the Hamilton filter with $k = 6$ years and the lag length p in the range from 1 to 4 quarters. For each regression, the table reports the slope estimate, the Newey–West corrected t-statistic (h lags), and the adjusted R^2 statistic. The regressions are estimated over the period 1955:Q4 to 2019:Q4 across all values of p.

	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Panel A. Investment Predictability							
$CC^{p=1}$	−0.029	−0.083	−0.266	−0.721	−1.079	−1.294	−1.451
t-Stat	−1.002	−1.400	−2.333	−3.009	−2.761	−2.579	−2.623
$\bar{R}^2$	−0.000	0.006	0.029	0.099	0.168	0.213	0.247
$CC^{p=2}$	−0.029	−0.083	−0.266	−0.722	−1.081	−1.299	−1.457
t-Stat	−0.999	−1.399	−2.328	−2.995	−2.756	−2.584	−2.633
$\bar{R}^2$	−0.000	0.006	0.029	0.099	0.168	0.214	0.249
$CC^{p=3}$	−0.029	−0.083	−0.266	−0.723	−1.083	−1.307	−1.464
t-Stat	−0.999	−1.413	−2.306	−2.960	−2.734	−2.585	−2.642
$\bar{R}^2$	−0.000	0.006	0.029	0.099	0.168	0.216	0.250
$CC^{p=4}$	−0.030	−0.084	−0.265	−0.723	−1.089	−1.319	−1.473
t-Stat	−1.025	−1.406	−2.262	−2.917	−2.719	−2.596	−2.656
$\bar{R}^2$	0.000	0.006	0.029	0.098	0.169	0.218	0.252
Panel B. Employment Predictability							
$CC^{p=1}$	−0.004	−0.020	−0.081	−0.251	−0.412	−0.554	−0.656
t-Stat	−0.375	−1.012	−2.048	−2.840	−2.849	−2.833	−2.766
$\bar{R}^2$	−0.003	0.001	0.022	0.090	0.166	0.234	0.277
$CC^{p=2}$	−0.004	−0.020	−0.082	−0.252	−0.414	−0.557	−0.660
t-Stat	−0.391	−1.027	−2.059	−2.844	−2.856	−2.844	−2.779
$\bar{R}^2$	−0.003	0.001	0.022	0.091	0.168	0.236	0.280
$CC^{p=3}$	−0.004	−0.021	−0.082	−0.254	−0.417	−0.562	−0.664
t-Stat	−0.415	−1.061	−2.053	−2.846	−2.863	−2.854	−2.789
$\bar{R}^2$	−0.003	0.001	0.022	0.091	0.170	0.239	0.283
$CC^{p=4}$	−0.004	−0.021	−0.082	−0.255	−0.422	−0.568	−0.670
t-Stat	−0.459	−1.056	−2.029	−2.850	−2.875	−2.871	−2.800
$\bar{R}^2$	−0.003	0.001	0.022	0.092	0.173	0.244	0.286

investment growth (Panel A) and low employment growth (Panel B) at long horizons, and that CC stays statistically significant across various specifications of k. Thus, consistent with the return predictability results in Atanasov et al. (2020), we generally find strong evidence of investment and employment predictability when k is specified at long horizons of several years.

Following the analysis in Hamilton (2018), we use 4 lagged values in equation (11) as the main specification, but our results are robust toward using a different number of lags in equation (11). In Table 7, we show results for alternative lag length specifications of 1–4 lags.[3] For all of these lag specifications, CC retains its predictive power for long-horizon investment and employment growth. Overall, the slope coefficients, t-statistics, and R^2 values do not vary much across the alternative lag length specifications. Consequently, we are able to conclude that the main predictability results are robust toward alternative specifications of the Hamilton filter.

[3]The Supplementary Material shows results for higher-order lags. It also shows results when assuming that consumption follows a random walk. In that case, the detrending procedure reduces to a difference filter, because, for large samples, the OLS estimates in equation (11) converge to $b_1 = 1$ and $b_2 = b_3 = b_4 = 0$.

V. International Evidence

We now turn to international evidence of whether time variation in the discount rate implies fluctuations in investment and employment. As far as we are aware, there have been no empirical tests of whether the discount rate predicts long-horizon investment and employment growth using data from other countries than the United States. The international evidence serves two purposes. First, it provides a robustness test of the U.S.-based results. Second, by pooling information across international markets, we should achieve more powerful tests, which in turn should produce more reliable estimates.

We extract the cyclical component of individual country-level consumption based on OECD volume estimates on total private consumption for the following countries: Belgium, Canada, Germany, France, Italy, Japan, the Netherlands, Sweden, Switzerland, and the United Kingdom. We use $k=6$ years as in our main specification above. We collect international total return indices in national currency from Morgan Stanley Capital International (MSCI) available since 1970. To proxy for the risk-free rate, we use 3-month treasury bill rates obtained from the Global Financial Database. From the OECD database, we obtain volume estimates on aggregate investment in local currency. From Oxford Economics, we obtain quarterly employment extending back to 1980.[4] To increase the power of the statistical tests and in turn obtain more accurate estimates, we estimate pooled regression models. Pooling the data is especially relevant given the relatively small international samples compared to the U.S. sample.

As a first step, we must ensure that cyclical consumption is a relevant candidate to track variation in expected returns across international stock markets. To examine whether this is the case, we estimate predictive return regressions across countries:

$$r_{j,t+h} = \alpha_j + \beta \mathrm{CC}_{j,t} + \varepsilon_{j,t+h}, \tag{14}$$

where $r_{j,t+h}$ is the h-period ahead logarithm excess return on the MSCI index for country j and $\mathrm{CC}_{j,t}$ is the cyclical consumption in country j. Panel A of Table 8 shows the results from pooled forecasting regressions where we allow for heterogeneous intercepts (country fixed effects) but constrain the slope coefficient to be the same across countries as in equation (14). The table reports the estimate of the slope coefficient, the associated 2-way clustered t-statistic, and the within R^2. Following the procedure of Thompson (2011), the standard errors are robust to heteroscedasticity as well as correlation along both the time and country dimensions. Similar to the U.S. evidence, the international evidence shows that CC predicts future stock returns with a negative sign. Cyclical consumption is statistically significant across all forecast horizons, and the predictive power as measured by the within R^2 tends to increase at longer horizons. These results suggest that CC is a relevant proxy for capturing time-varying expected returns across international stock markets.

[4]We let the sample start in 1970 when predicting stock returns and investment growth, while the sample starts in 1980 when predicting employment growth due to data availability.

TABLE 8
International Evidence

Table 8 presents results from pooled predictive regressions using cyclical consumption to predict either logarithm returns (Panel A), logarithm investment growth (Panel B), or logarithm employment growth (Panel C). The forecast horizon ranges from 1 quarter ($h=1$) to 5 years ($h=20$). The cross section of countries includes the G10 countries except the United States. The time period is 1970:Q1 to 2019:Q4 for returns and investments (Panel A and B) and 1980:Q1 to 2019:Q4 for employment (Panel C). For each regression, the table reports the slope estimate, the associated t-statistic, and the within R^2. Following the procedure of Thompson (2011), the standard errors are robust to heteroscedasticity as well as correlation along both the time and country dimensions.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Panel A. Return Predictability							
CC	−0.287	−0.572	−1.105	−1.868	−2.392	−2.689	−2.690
t-Stat	−3.663	−3.604	−3.789	−4.089	−4.171	−4.848	−5.544
R^2_{within}	0.020	0.037	0.066	0.095	0.111	0.113	0.099
Panel B. Investment Predictability							
CC	−0.010	−0.042	−0.137	−0.392	−0.648	−0.875	−1.028
t-Stat	−1.639	−2.658	−3.666	−4.249	−3.965	−3.737	−3.736
R^2_{within}	0.000	0.003	0.014	0.055	0.099	0.144	0.173
Panel C. Employment Predictability							
CC	0.008	0.011	0.004	−0.052	−0.133	−0.214	−0.280
t-Stat	2.454	1.559	0.235	−1.768	−3.092	−3.313	−3.418
R^2_{within}	0.010	0.006	0.000	0.016	0.062	0.118	0.166

Next, we estimate the following predictive regressions:

$$\Delta i_{j,t+h} = \alpha_j + \beta \text{CC}_{j,t} + \varepsilon_{j,t+h}, \tag{15}$$

$$\Delta e_{j,t+h} = \alpha_j + \beta \text{CC}_{j,t} + \varepsilon_{j,t+h}, \tag{16}$$

where $\Delta i_{j,t+h}$ and $\Delta e_{j,t+h}$ are the h-period ahead logarithm growth in investment and employment for country j, respectively. Panel B of Table 8 shows the results of estimating equation (15) over the period 1970:Q1 to 2019:Q4. In line with the U.S. evidence, the international evidence shows that there is a negative relation between cyclical consumption and long-horizon investment growth. The coefficient estimate on cyclical consumption is insignificant at the 1-quarter horizon, but turns significant at the 2-quarter horizon, although the within R^2 is still quite low at this horizon. The ability of CC to predict investment growth gets stronger at longer horizons with the R^2 rising to 0.17 at the 5-year horizon, similar to that recorded in the United States. The results imply that an increase in CC, which corresponds to a decrease in the discount rate, predicts country-level investments to fall in the long run – a finding that is entirely consistent with the U.S. results. The extent of the predictability as measured by the R^2 indicates an important role for the discount rate in investment decisions across a wide cross section of countries.

We turn now to employment predictability and show the results of estimating equation (16) over the period 1980:Q1 to 2019:Q4 in Panel C of Table 8. At the 1-quarter horizon, we observe a significantly positive relation between CC and employment growth, but with a modest degree of predictive power as measured by the within R^2 of 0.01. The predictive relation between CC and employment growth turns negative at the 3-year horizon and onward. We also observe that the predictive power of CC strengthens at longer horizons with within R^2s of 0.06, 0.12, and

0.17 at 3-, 4-, and 5-year horizons, respectively. Accordingly, the international evidence confirms that long-horizon employment growth reacts to the discount rate in a way that is consistent with the dynamic model of Chen and Zhang (2011). The results for the international evidence are very similar to the U.S. evidence with the major exception that at the short horizon, there is an initial increase in employment growth for the international sample, consistent with the theoretical predictions in Chen and Zhang (2011).

The evidence discussed previously in Table 8 uses data from 1970 for investment and 1980 for employment using quarterly data. The international sample is therefore somewhat shorter than the U.S. quarterly data that are available from 1947. It is possible to analyze data from an earlier point in time by examining annual data on international employment and investment growth extending back to 1960. These data are from the OECD database. This annual data set provides a sample period closer to that of the United States.

Table 9 presents the results from annual pooled predictive regressions using annual cyclical consumption to predict either annual logarithm investment growth (Panel A) or annual logarithm employment growth (Panel B). The forecast horizon ranges from 1 ($h = 1$) to 5 years ($h = 5$). Given the construction of annual CC, the time period used to estimate the investment and employment regressions is 1966–2019. For each regression, the table reports the coefficient estimate, the associated 2-way clustered t-statistic, and the within R^2.

The results with annual data over the longer sample period presented in Table 9 are consistent with those using quarterly data. For investment in Panel A, the coefficient at the 1-year horizon is negative, but it is not statistically significant. At the 2-year horizon and up to the 5-year horizon, the coefficient estimates are all negative and statistically significant. The extent of investment growth predictability increases with the horizon with R^2s increasing from 0.03 at the 2-year horizon to 0.13 at the 5-year horizon, consistent with the results using quarterly data.

Panel B of Table 9 reveals evidence of employment growth predictability using annual data that are consistent with that using quarterly data. There is a

TABLE 9

International Evidence: Annual Data

Table 9 presents results from annual pooled predictive regressions using cyclical consumption to predict either logarithm investment growth (Panel A) or logarithm employment growth (Panel B). The forecast horizon ranges from 1 ($h = 1$) to 5 years ($h = 5$). The cross section of countries includes the G10 countries except the United States. The time period is 1966–2019. For each regression, the table reports the slope estimate, the associated t-statistic, and the within R^2. Following the procedure of Thompson (2011), the standard errors are robust to heteroscedasticity as well as correlation along both the time and country dimensions.

	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$
Panel A. Investment Predictability					
CC	−0.031	−0.270	−0.523	−0.752	−0.928
t-Stat	−0.800	−3.927	−4.283	−4.025	−3.969
R^2_{within}	0.001	0.027	0.063	0.099	0.126
Panel B. Employment Predictability					
CC	0.026	−0.015	−0.088	−0.176	−0.254
t-Stat	1.565	−0.474	−1.735	−2.225	−2.478
R^2_{within}	0.008	0.001	0.019	0.055	0.091

positive coefficient estimate at the 1-year horizon, which is not statistically significant. The coefficient estimates then become negative at the remaining horizons, and they are statistically significant at the 4- and 5-year horizons. Extending the sample period with annual data confirms the earlier results using quarterly data over a shorter sample.

Taken together, the extent of investment and employment predictability across countries is similar in magnitude and significance to that obtained using U.S. data. The results imply that time variation in the discount rate is important in determining future investment and employment dynamics across the G10 countries, providing strong support for the dynamic models of investment and employment developed by Lettau and Ludvigson (2002) and Chen and Zhang (2011).

VI. Conclusion

Dynamic models of employment and investment growth imply that discount rate variation should affect the employment and investment decisions that firms make. However, the evidence to date is limited, which is puzzling for various reasons. First, theoretical models point to an important role for discount rates in dynamic models of employment and investment. Second, investment and employment show substantial variation over time. Third, discount rate fluctuations account for a substantial proportion of stock price movements (Cochrane (2011)). A key challenge in analyzing the implications of employment and investment models is to come up with an appropriate proxy for discount rate variation, because stock return predictor variables often exhibit unstable predictive power (see, e.g., Goyal and Welch (2008), Henkel et al. (2011)). To overcome this challenge, we use cyclical consumption to track discount rate variation, as this variable contains robust and strong predictive power for stock returns and hence is a suitable proxy for capturing time-varying discount rates (see Atanasov et al. (2020)).

We provide a host of empirical results that support both the Lettau and Ludvigson (2002) model of investment dynamics and the Chen and Zhang (2011) model of employment dynamics. The main results focus on the U.S. and are supported by a wide variety of robustness tests. We also provide international evidence that the long-run model implications of Lettau and Ludvigson (2002) and Chen and Zhang (2011) are confirmed using a wide cross section of developed countries.

The empirical results that we present indicate that firms react rationally to discount rate variation, and that the discount rate variation is important in understanding macroeconomic dynamics like investment and employment.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109021000715.

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