# 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 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.

**JEL Classification**: E22; G12; J01

**Keywords**: discount rates; investment growth; employment growth; cyclical consumption.

# 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 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 paper, Atanasov,

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[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, that

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 paper 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 both 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 U.S. The international results show that

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is, during business cycle expansions.

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 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 paper is organized as follows. The next section 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, for example, Jermann (1998) and Jermann (2010)) and the value effect (Zhang (2005) and 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, for example, Hou, Xue, and Zhang (2015), Hou, Xue, and Zhang (2020), and Hou, Mo, Xue, and Zhang (2021)).

In search models of employment such a 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 (2021) 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 paper 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 below.

## 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

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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 multi-period model works, we follow Lettau and Ludvigson (2002) who derive the following expression for the natural log of Tobin's $Q$, $q_t$:

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

where $q_t$ is expressed as a first order function of expected marginal profits, $m_{t+1+j}$, and expected future investment returns, $r_{it+1+j}$. $\phi_{t+j}$ contains variance and covariance terms along with linearization constants, and $\rho_q = 1/ \left( 1 + \exp \left( \overline{m - q} \right) \right)$. 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 $p_t$:

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

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:

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

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:

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

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

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

Now from (3) and (5) it is clear that a variable that forecasts long horizon stock returns

such as $DP_t$ in (3) can also be used to forecast long horizon variation in $\Delta q_t$. 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 (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 one 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 $\Delta q_{t+1+j}$ on the right hand side of (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's (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 (5) above 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:

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

where $\Delta i_{t+h} = i_{t+h} - i_t$ is $h$-period ahead log growth in investment, $Z_t$ is a discount rate

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proxy, and $\varepsilon_{t+h}$ 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 one-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 $t$ implies 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:

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

where $a > 0$, $N_t$ is total employment, $J_t$ represents job vacancies, and $\lambda_t$ is the probability

that a vacancy will be filled. Given separation rates, $s$, happen at a constant rate between zero and one, the stock of employment evolves according to

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

This relation is important since it embodies a one 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 increases 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:

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

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 $R_{t+1}^H$ 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

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growth with the following regression:

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

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

## III. Data

Data on investment is private nonresidential investment (seasonally adjusted and inflation adjusted) available from the Bureau of Economic Analysis. Data on employment is private nonfarm payrolls which exclude government employees (seasonally adjusted) available from the Bureau of Labor Statistics. We calculate the growth rate of the natural log 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 log of real per capita consumption, $c_t$, on a constant and four lagged values

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[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), and 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.

of consumption as of date $t - k$:

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

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

(12)
$$CC_t = c_t - \widehat{b_0} - \widehat{b_1} c_{t-k} - \widehat{b_2} c_{t-k-1} - \widehat{b_3} c_{t-k-2} - \widehat{b_4} c_{t-k-3}.$$

Since $CC_t$ is computed based on a one-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).

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 six years in the detrending filter is consistent with implications of the Campbell and Cochrane (1999) external habit formation model. We estimate (11) over the period 1947Q1 to 2019Q4 and then compute $CC_t$ using (12) with $k = 24$ quarters, implying that the first observation on $CC_t$ is for 1953Q4 and the last is for 2019Q4.

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.

Insert Figure 1 here.

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 log dividend-price ratio (DP) which is the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of prices on the S&P 500 index; the term spread (TMS) which is the long-term yield on government bonds minus the three-month treasury bill rate; the default yield spread (DFY) which is the difference between BAA- and AAA-rated corporate bond yields; the three-month treasury bill rate (TBL); and the consumption-wealth ratio (CAY) which is the residual from a cointegrating relation between log consumption, log asset (nonhuman) wealth, and log labor income (Lettau and Ludvigson (2001)). Data on these variables are available from the Goyal and Welch (2008) dataset.

There are also four 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 log 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 log growth rate (DGDP). Data on these variables are available from the FRED database of the St. Louis Federal Reserve Bank.

## A. 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:

$$(13) \qquad\qquad r_{t+h} = \alpha + \beta Z_t + \varepsilon_{t+h},$$

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

Insert Table 1 here.

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 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 one standard deviation below its mean leads to a rise in the expected return of about six percentage points at an annual rate. This evidence suggests substantial discount rate variation. The estimate of the coefficient at the one quarter horizon is strongly statistically significant and the associated $\bar{R}^2$ 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

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is low in bad times. The coefficient estimates are statistically significant at all horizons and the $\bar{R}^2$ rises to 0.44 at the twenty 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 four 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, while 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.

Insert Table 2 here.

Panel A in 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 one and two quarter horizons are not statistically significant, the coefficient estimate at the four quarter horizon is statistically significant but CC only has a minor impact with an $\overline{R}^2$ of 0.03. However, at horizons of eight quarters and longer the estimated coefficients are highly statistically significant and the $\overline{R}^2$ ranges from 0.11 at the eight quarter horizon to 0.22 at the twenty 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) model. As well as having a large impact in terms of explanatory power, the economic impact is also large. For example, a one standard deviation movement in the discount rate, which is 4.4%, leads to a change in investment based on the eight quarter horizon estimate of 1.6% per annum, which is a substantial amount compared on 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. 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

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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 eight to sixteen quarters. Higher values of TMS, which predicts higher stock returns, predicts 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 one 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 five-year horizon. In addition, the other predictive variables often have significant predictive power at short and medium-term horizons of up to three years.

Panel A in 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 one and two quarter horizons. There is evidence of predictability at the four 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 eight

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or more quarters. The $\overline{R}^2$ increases from 0.10 at the eight quarter horizon to 0.26 at the twenty quarter horizon. The economic effect of a one 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%.

Insert Table 3 here.

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 four and five 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 one to four 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 the fourth to twentieth 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 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

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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 both 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 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 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, for example, 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 the 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 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 eight 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 twenty 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 twelve 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 the 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 $q$

have 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 the 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 to that of CC.

## B. Robustness Tests

In this section, we perform two 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 versus 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 towards 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 repeat the results already presented using nondurable consumption. The next set of results shows rather limited predictive power of investment growth when measuring consumption based upon 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 as 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 as 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 towards using alternative measures of consumption, although the predictability is reduced when combining services with other measures of consumption.

## 2. The Hamilton Filter

We use the Hamilton (2018) filter as our preferred approach to detrend consumption because it is a simple one-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 (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 lead to stock return predictability. To check the robustness towards the specification of $k$, Table 6 shows results from predicting investment growth and employment growth for values of $k$ in the range from three to ten years. The results show that high current consumption relative to past consumption (high CC values) predicts low investment growth (Panel A) and low employment growth (Panel B) at long horizons and that CC stays statistically significant across the 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.

Insert Table 6 here.

Following the analysis in Hamilton (2018), we use four lagged values in (11) as the main specification, but our results are robust towards using a different number of lags in (11). In Table 7, we show results for alternative lag length specifications of $1, 2, 3$ and $4$ 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 towards alternative specifications of the Hamilton filter.

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[3]The online appendix 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 (11) converge to $b_1 = 1$ and $b_2 = b_3 = b_4 = 0$.

Insert Table 7 here.

# 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 U.S. 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, Netherlands, Sweden, Switzerland, and the UK. 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 three-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

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[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.

to track variation in expected returns across international stock markets. To examine whether this is the case, we estimate predictive return regressions across countries:

$$(14) \qquad\qquad r_{j,t+h} = \alpha_j + \beta\text{CC}_{j,t} + \varepsilon_{j,t+h},$$

where $r_{j,t+h}$ is the $h$-period ahead log excess return on the MSCI index for country $j$ and $\text{CC}_{j,t}$ is cyclical consumption in country $j$. Panel A in Table 8 shows 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 (14). The table reports the estimate of the slope coefficient, the associated two-way clustered $t$-statistic, and the within $R^2$. Following the procedure of Thompson (2011), the standard errors are robust to heteroskedasticity as well as correlation along both the time and the country dimension. 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.

Insert Table 8 here.

Next, we estimate the following predictive regressions:

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

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

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where $\Delta i_{j,t+h}$ and $\Delta e_{j,t+h}$ are the $h$-period ahead log growth in investment and employment for country $j$. Panel B in Table 8 shows results of estimating (15) over the period 1970Q1 to 2019Q4. 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 short horizons of one and two quarters, but turns significant at the four 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 five-year horizon, similar to that recorded in the U.S. 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 (16) over the period 1980Q1 to 2019Q4 in Panel C in Table 8. At the one-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 two-year horizon and onwards. We also observe that the predictive power of CC strengthens at longer horizons with within $R^2$s of 0.06, 0.12, and 0.17 at the three-, four-, and five-year horizon. 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 above 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 is 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 U.S.

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

Insert Table 9 here.

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 one year horizon is negative but it is not statistically significant. At the two year horizon and up to the five year horizon, the coefficient estimates are all negative and statistically significant. The extent of investment growth predictability increases with the horizon with $R^2$s increasing from 0.03 at the two year horizon to 0.13 at the five year horizon, consistent with the results using quarterly data.

Panel B of Table 9 reveals evidence of employment growth predictability using an-

nual data that is consistent with that using quarterly data. There is a positive coefficient estimate at the one year horizon which is not statistically significant. The coefficient estimates then become negative at the remaining horizons and they are statistically significant at the four and five 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) and 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.

# References

Abel, A. B., and O. Blanchard. "The Present Value of Profits and Cyclical Movements in Investment." *Econometrica* 54 (1986), 246-273.

Atanasov, V.; S. V. Møller; and R. Priestley. "Consumption Fluctuations and Expected Returns." *Journal of Finance* 75 (2020), 1677-1713.

Bai, H, and L. Zhang. "Searching for the Equity Premium." *Journal of Financial Economics*, forthcoming (2021).

Barro, R. J. "The Stock Market and Investment." *Review of Financial Studies* 3 (1990), 115-131.

Barro, R. J. "Rare Disasters and Asset Markets in the Twentieth Century." *Quarterly Journal of Economics* 121 (2006), 823-866.

Blanchard, O. J.; C. Rhee; and L. H. Summers. "The Stock Market, Profit and Investment." *Quarterly Journal of Economics* 108 (1993), 115-136.

Campbell, J. Y., and J. H. Cochrane. "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." *Journal of Political Economy* 107 (1999), 205-251.

Campbell, J. Y., and R. Shiller. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors." *Review of Financial Studies* 1 (1988), 195-227.

Chen, L, and L. Zhang. "Do Time-Varying Risk Premiums Explain Labor Market Performance?" *Journal of Financial Economics* 99 (2011), 385-399.

Cochrane, J. H. "Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations." *Journal of Finance* 46 (1991), 207-234.

Cochrane, J. H. "Discount Rates." *Journal of Finance* 66 (2011), 1047-1108.

Cochrane, J. H. "Macro-Finance." *Review of Finance* 21 (2017), 945-985.

Cooper, I. "Asset Pricing Implications of Non-Convex Adjustment Costs and Irreversibility of Investment." *Journal of Finance* 61 (2006), 139-170.

Dangl, T., and M. Halling. "Predictive Regressions With Time-Varying Coefficients." *Journal of Financial Economics* 106 (2012), 157-181.

Golez, B., and P. Koudijs. "Four Centuries of Return Predictability." *Journal of Financial Economics* 127 (2018), 248-263.

Goyal, A., and I. Welch. "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction." *Review of Financial Studies* 21 (2008), 1455-1508.

Hall, R. E. "High Discounts and High Unemployment." *American Economic Review* 107 (2017), 305-330.

Hamilton, J. D. "Why You Should Never Use the Hodrick-Prescott Filter." *Review of Economics and Statistics* 100 (2018), 831-843.

Henkel, S. J.; S. Martin; and F. Nardari. "Time-Varying Short-Horizon Predictability." *Journal of Financial Economics* 99 (2011), 560-580.

Hou, K.; H. Mo; C. Xue; and L. Zhang. "An Augmented $Q$-Factor Model With Expected Growth." *Review of Finance* 25 (2021), 1-41.

Hou, K.; C. Xue; and L. Zhang. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies* 28 (2015), 650-705.

Hou, K.; C. Xue; and L. Zhang. "Replicating Anomalies." *Review of Financial Studies* 33 (2020), 2019-2133

Jermann, U. J. "Asset Pricing in Production Economies." *Journal of Monetary Economics* 41 (1998), 257-275.

Jermann, U. J. "The Equity Premium Implied by Production." *Journal of Financial Economics* 98 (2010), 279-296.

Kroencke, T. "Asset Pricing Without Garbage." *Journal of Finance* 72 (2017), 47-98.

Lamont, O. "Investment Plans and Stock Returns." *Journal of Finance* 55 (2000), 2719-2745

Lettau, M., and S. C. Ludvigson. "Consumption, Aggregate Wealth and Expected Stock Returns." *Journal of Finance* 66 (2001), 815-849.

Lettau, M., and S. C. Ludvigson. "Time-Varying Risk Premia and the Cost of Capital: An Alternative Implication of the Q Theory of Investment." *Journal of Monetary Economics* 49 (2002), 31-66.

Li, J.; H. Wang; and J. Yu. "Aggregate Expected Investment Growth and Stock Market Returns." *Journal of Monetary Economics* 117 (2021), 618-638.

Liu, L. X.; T. M. Whited; and L. Zhang. "Investment-Based Expected Stock Returns." *Journal of Political Economy* 117 (2009), 1105-1139.

Merz, M., and E. Yashiv. "Labor and the Market Value of the Firm." *American Economic Review* 97 (2007), 1419-1431.

Mortensen, D. T., and C. A. Pissarides. "Job Creation and Job Destruction in the Theory of Unemployment." *Review of Economic Studies* 61 (1994), 397-415.

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (1987), 703-708.

Petrosky-Nadeau, N.; L. Zhang; and L. A. Kuehn. "Endogenous Disasters." *American Economic Review* 108 (2018), 2212-2245.

Rapach, D.E.; J. K. Strauss; and G. Zhou. "Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy." *Review of Financial Studies* 23 (2010), 821-862.

Rietz, T. A. "The Equity Risk Premium: A Solution." *Journal of Monetary Economics*

22 (1988), 117-131.

Savov, A. "Asset Pricing With Garbage." *Journal of Finance* 66 (2011), 177-201.

Thompson, S. B. "Simple Formulas for Standard Errors that Cluster by Both Firm and Time." *Journal of Financial Economics* 99 (2011), 1-10.

Tobin, J. "A General Equilibrium Approach to Monetary Theory." *Journal of Money, Credit, and Banking* 1 (1969), 15-29.

Wilcox, D. W. "The Construction of US Consumption Data: Some Facts and Their Implications for Empirical Work." *American Economic Review* 82 (1992), 922-941.

Yashiv, E. "The Determinants of Equilibrium Unemployment." *American Economic Review* 90 (2000), 1297-1322.

Zhang, L. "The Value Premium." *Journal of Finance* 110 (2005), 67-103.

## Table 1. Predicting Discount Rates

The table presents results of predictive regressions, $r_{t+h} = \alpha + \beta Z_t + \varepsilon_{t+h}$, where $r_{t+h}$ is the $h$-quarter ahead log 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 t-bill rate (TBL), and the consumption-wealth ratio (CAY). 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 1953Q4 to 2019Q4.

|  | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
|---|---|---|---|---|---|---|---|
| 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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | 0.013 | 0.029 | 0.052 | 0.081 | 0.112 | 0.145 | 0.152 |

## Table 2. Investment Predictability

Panel A and B present results of univariate predictive regressions, $\Delta i_{t+h} = i_{t+h} - i_t = \alpha + \beta Z_t + \varepsilon_{t+h}$, where $\Delta i_{t+h}$ is the $h$-quarter ahead log growth in investments and $Z_t$ is a predictive variable. Panel A shows results using cyclical consumption (CC) as predictive variable, while 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 1953Q4 to 2019Q4.

| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
|---|---|---|---|---|---|---|---|
| **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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | 0.001 | 0.007 | 0.019 | 0.037 | 0.043 | 0.047 | 0.046 |

(Continued)

| Panel C: Multivariate Regressions With CC and CAY | | | | | | |
|---|---|---|---|---|---|---|
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| 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 |
| $\overline{R}^2$ | -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 | | | | | | |
|---|---|---|---|---|---|---|
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| 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 |
| $\overline{R}^2$ | 0.273 | 0.241 | 0.187 | 0.215 | 0.246 | 0.257 | 0.261 |

## Table 3. Employment Predictability

Panel A and B present results of univariate predictive regressions, $\Delta e_{t+h} = e_{t+h} - e_t = \alpha + \beta Z_t + \varepsilon_{t+h}$, where $\Delta e_{t+h}$ is the $h$-quarter ahead log growth in employment and $Z_t$ is a predictive variable. Panel A shows results using cyclical consumption (CC) as predictive variable, while 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 1953Q4 to 2019Q4.

| Panel A: Univariate Regressions With CC | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| 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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | 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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -0.003 | -0.002 | 0.002 | 0.003 | -0.001 | -0.004 | -0.003 |

(Continued)

| Panel C: Multivariate Regressions With CC and CAY | | | | | | |
|---|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| 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 |
| $\overline{R}^2$ | -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 | | | | | | |
|---|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| 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 |
| $\overline{R}^2$ | 0.178 | 0.163 | 0.172 | 0.268 | 0.318 | 0.348 | 0.392 |

## Table 4. Macroeconomic Controls

Panel A and B present results from predictive regressions of the $h$-period ahead log 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 estimate, the Newey-West corrected $t$-statistic ($h$ lags), and the adjusted $R^2$ statistic. The regressions are estimated over the period 1953Q4 to 2019Q4.

| Panel A: Investment Predictability | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| 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 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| 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 |

### Table 5. Alternative Consumption Measures

Panel A and B present results from predictive regressions of the $h$-period ahead log 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 $R^2$ statistic. The regressions are estimated over the period 1953Q4 to 2019Q4.

| Panel A: Investment Predictability | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| $CC^{nd}$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -0.004 | -0.001 | 0.013 | 0.060 | 0.114 | 0.141 | 0.164 |

Panel B: Employment Predictability

|  | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
|---|---|---|---|---|---|---|---|
| $\mathrm{CC^{nd}}$ | -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 |
| $\overline{R}^2$ | -0.003 | 0.001 | 0.026 | 0.101 | 0.165 | 0.213 | 0.261 |
| $\mathrm{CC^{serv}}$ | 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 |
| $\overline{R}^2$ | 0.003 | -0.001 | -0.004 | 0.008 | 0.021 | 0.026 | 0.041 |
| $\mathrm{CC^{dur}}$ | 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 |
| $\overline{R}^2$ | 0.013 | 0.007 | -0.003 | 0.012 | 0.074 | 0.141 | 0.216 |
| $\mathrm{CC^{ndser}}$ | 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 |
| $\overline{R}^2$ | -0.001 | -0.004 | 0.001 | 0.031 | 0.057 | 0.072 | 0.098 |
| $\mathrm{CC^{goods}}$ | 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 |
| $\overline{R}^2$ | -0.001 | -0.004 | 0.001 | 0.047 | 0.122 | 0.192 | 0.267 |
| $\mathrm{CC^{total}}$ | 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 |
| $\overline{R}^2$ | 0.002 | -0.002 | -0.002 | 0.025 | 0.068 | 0.102 | 0.145 |

**Table 6. Cycle Length**

Panel A and B present results from predictive regressions of the $h$-period ahead log growth in investment and employment, respectively. As predictive variable, we use cyclical consumption extracted using different values of the cycle length parameter $k$: three years (3y), four years (4y), five years (5y), six years (6y), seven years (7y), eight years (8y), nine years (9y), and ten 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 1957Q4 to 2019Q4 across all values of $k$.

| Panel A: Investment Predictability | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| $CC^{3y}$ | 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

| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
|---|---|---|---|---|---|---|---|
| $CC^{3y}$ | 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 |

## Table 7. Lag Length Specification

Panel A and B present results from predictive regressions of the $h$-period ahead log 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 1955Q4 to 2019Q4 across all values of $p$.

| Panel A: Investment Predictability | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| $CC^{p=1}$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | 0.000 | 0.006 | 0.029 | 0.098 | 0.169 | 0.218 | 0.252 |
| Panel B: Employment Predictability | | | | | | | |
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ | $h = 12$ | $h = 16$ | $h = 20$ |
| $CC^{p=1}$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -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 |
| $\overline{R}^2$ | -0.003 | 0.001 | 0.022 | 0.092 | 0.173 | 0.244 | 0.286 |

## Table 8. International Evidence

The table presents results from pooled predictive regressions using cyclical consumption to predict either log returns (Panel A), log investment growth (Panel B), or log employment growth (Panel C). The forecast horizon ranges from one quarter ($h = 1$) to five years ($h = 20$). The cross-section of countries includes the G10 countries except the U.S. The time period is 1970Q1 to 2019Q4 for returns and investments (Panel A and B) and 1980Q1 to 2019Q4 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 heteroskedasticity as well as correlation along both the time and the country dimension.

| Panel A: Return Predictability | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| CC | -0.287 | -0.572 | -1.105 | -1.868 | -2.392 | -2.689 | -2.690 |
| $t$-stat | -6.365 | -6.300 | -6.476 | -6.247 | -6.309 | -6.279 | -5.682 |
| $R^2_{within}$ | 0.020 | 0.037 | 0.066 | 0.095 | 0.111 | 0.113 | 0.099 |
| Panel B: Investment Predictability | | | | | | | |
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| CC | -0.010 | -0.042 | -0.137 | -0.392 | -0.648 | -0.875 | -1.028 |
| $t$-stat | -1.017 | -1.894 | -3.055 | -5.033 | -6.198 | -6.246 | -6.265 |
| $R^2_{within}$ | 0.000 | 0.003 | 0.014 | 0.055 | 0.099 | 0.144 | 0.173 |
| Panel C: Employment Predictability | | | | | | | |
| | $h=1$ | $h=2$ | $h=4$ | $h=8$ | $h=12$ | $h=16$ | $h=20$ |
| CC | 0.008 | 0.011 | 0.004 | -0.052 | -0.133 | -0.214 | -0.280 |
| $t$-stat | 2.304 | 1.387 | 0.210 | -1.692 | -3.548 | -5.016 | -5.810 |
| $R^2_{within}$ | 0.010 | 0.006 | 0.000 | 0.016 | 0.062 | 0.118 | 0.166 |

## Table 9. International Evidence: Annual Data

The table presents results from annual pooled predictive regressions using cyclical consumption to predict either log investment growth (Panel A) or log employment growth (Panel B). The forecast horizon ranges from one year ($h = 1$) to five years ($h = 5$). The cross-section of countries includes the G10 countries except the U.S. The time period is 1966 to 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 heteroskedasticity as well as correlation along both the time and the country dimension.

| Panel A: Investment Predictability | | | | | |
|---|---|---|---|---|---|
| | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ | $h = 5$ |
| CC | -0.031 | -0.270 | -0.523 | -0.752 | -0.928 |
| $t$-stat | -0.624 | -3.608 | -5.627 | -6.133 | -6.409 |
| $R^2_{within}$ | 0.001 | 0.027 | 0.063 | 0.099 | 0.126 |
| Panel B: Employment Predictability | | | | | |
| | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ | $h = 5$ |
| CC | 0.026 | -0.015 | -0.088 | -0.176 | -0.254 |
| $t$-stat | 1.397 | -0.413 | -1.705 | -2.650 | -3.291 |
| $R^2_{within}$ | 0.008 | 0.001 | 0.019 | 0.055 | 0.091 |

**Figure 1. Cyclical Consumption**