The Role of the Discount Rate in Investment and Employment Decisions

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Abstract

We show that a decrease (increase) in the discount rate predicts both higher (lower) investment and employment growth in the short run. In the long run, we observe the opposite pattern. These novel findings are consonant with dynamic models of investment and employment. The predictability by the discount rate is substantial making it a key source of business cycle fluctuations. The patterns of predictability are consistent with differences in the adjustment costs between investment and employment. They are also consistent with differences in the adjustment costs of hiring and firing and the adjustment costs of increasing and decreasing investment.

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1 Introduction

Predictions from standard models of investment and employment fail to capture movements in actual investment and employment growth. For example, Tobin's (1969) Q model of investment that predicts an increase (decrease) in investment when the discount rate falls (rises) fails in the data. Similarly, the search and matching model of Mortensen and Pissarides (1994) which has dominated research in labor markets cannot explain fluctuations in employment through its main component of productivity.

Production based models of asset prices that involve frictions in the form of adjustment costs offer an alternative mechanism to help explain both investment and employment growth. Lettau and Ludvigson (2002) derive a dynamic model that relates the discount rate to long run investment growth. Chen and Zhang (2011) derive a dynamic model that relates the discount rate to both short and long term employment growth. In these models, if the discount rate varies, firms' investment and employment decisions should be affected in the long run in the opposite direction to that of the short run. While both of these models provide novel and interesting insights, unfortunately, the empirical evidence to support both models is limited so far. Lettau and Ludvigson (2002) find some evidence of a long run role for the discount rate in investment growth. Chen and Zhang (2011) find some evidence of a short run role for the discount rate on employment growth. However, these effects disappear when controlling for standard macroeconomic variables. Furthermore, both Lettau and Ludvigson (2002) and Chen and Zhang (2011) ignore how adjustment costs of investment and labor could impact on how the size and sign of discount rate movements affect investment and employment growth. It still remains a puzzle why discount rate variation today, which appears to be substantial in the data and the major component of a firm's cost of capital, has no discernible affect on employment or investment decisions of corporate managers.

In this paper, exploiting new insights into how to measure discount rate variation and taking into account adjustment costs of investment and employment in our analysis, we show for the first time that short-run and long-run implications of the Lettau and Ludvigson (2002) and Chen and Zhang (2011) dynamic models of investment and employment are confirmed in the data. In the short run, both investment and employment growth increase when the discount rate falls and decrease when the discount rate rises. In the long run, as predicted by the dynamic models, we find the opposite pattern. The impact of the discount rate is substantial, both economically and statistically. This suggests that corporate managers respond rationally to variations in their firm's cost of capital when making investment and employment decisions. In turn, this indicates that discount rate variation can have a major impact on business cycle fluctuations.

We also provide novel evidence that the reaction of firms to whether the discount rate increases or decreases is consistent with differences in adjustment costs of investment and employment. First, we find that employment growth is more sensitive to short run changes in the discount rate than investment growth, suggesting that the adjustment costs of employment are lower than those of investment. Second, employment growth reacts in the short run to both large and small changes in the discount rate but investment growth reacts only to large changes also suggesting that the adjustment costs of investment are higher than the adjustment costs of employment. Third, an increase in the discount rate has a larger short run impact on employment growth than a decrease in the discount rate. This suggests that the adjustment costs of firing are lower than those of hiring. Fourth, large decreases in the discount rate have only a marginal impact in the short run on increasing investment, whereas a large increase in the discount rate has a big impact on decreasing investment growth. This suggests that adjustment costs of increasing investment are higher than those of reducing investment.

The crucial element in assessing the ability of production based models to explain investment and employment dynamics is to be able to accurately measure discount rate variation over the business cycle. 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, Møller, and Priestley (2019) 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 results in Atanasov, Møller, and Priestley (2019) document substantial discount rate variation in both good and bad economic times, over short and long horizons, and is stable across time. This 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 leads to a better understanding of how the discount rate affects business cycle fluctuations.

Using this new predictor of the discount rate, we show that there is strong evidence of both short run and long run predictability that is consistent with dynamic models of

[1] Goyal and Welch (2007) 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 is, during business cycle expansions.

investment and hiring. We find that a decrease (increase) in the discount rate predicts higher (lower) investment and labour growth in the short run as well as predicting lower (higher) investment and labour growth in the long run. We record an $\overline{R}^2$ of 0.06 at the one quarter horizon for investment growth rising monotonically to 0.33 at the five year horizon. For labour growth we record an $\overline{R}^2$ of 0.12 at the one quarter horizon suggesting that labour reacts more strongly to discount rate changes than investment in the short run. At the five year horizon the $\overline{R}^2$ is 0.26. The economic impact of discount rate movements on investment and labour growth are substantial with a one standard deviation movement in the discount rate leading to a change in investment of 1.7% per annum and a change in employment of 0.5% per annum.

The findings are robust to how we derive discount rate movements. For example, we find similar results if we use predictive regressions with direct proxies for the discount rate or if we generate discount rate news using Campbell's (1991) decomposition of unexpected returns from the present value model (see Campbell and Vuolteenaho (2004)). The decomposition of unexpected returns has the advantage of also allowing us to compare the impact of cash flow news (future profitability) on employment and investment decisions. Investment growth is affected in the short run by news about both discount rates and cash flows. Employment growth is affected only by news about discount rates.

A central feature of the dynamic models of investment and employment is that there are adjustment costs of increasing and decreasing investment and employment. There are various types of adjustment costs. Non-convex adjustment costs mean that firms only invest and hire when business conditions are sufficiently good and only fire and disinvest when they are sufficiently bad. So with these types of costs, there is an inaction period which will be determined in part by the size of the discount rate movement. The implication of this is that the discount rate might have to change by a sufficiently large amount if there is to be an impact on employment and investment rates. The inaction area is the real option value of waiting that is greater than the returns from investment and hiring. This is typical of disaggregated investment where investment spikes might be observed. Convex adjustment costs give a smooth investment series typically observed in the aggregate data.

There are also adjustment costs that are based om partial irreversibilities. In the employment models the partial irreversibilities are due to hiring, training and firing costs and can be measured as a fraction of the wage. In investment models, partial irreversibilities arise from resale losses due to transaction costs, the market for lemons, fire sales, and the physical costs of resale. When firms make new investment and hiring, this gives rise to fixed disruption costs where both new capital and labour will entail a disruption in production as they are installed which can be measured as a fixed cost loss of output. The fixed costs of hiring can come from advertising, interviewing and training. The fixed costs of investment could be that production is halted. Cooper and Haltiwanger (2006) find that a model which mixes both convex and non-convex adjustment costs fits the data best.

Bloom (2009) finds moderate non-convex labour adjustment costs and substantial non-convex adjustment costs of investment at the firm level. That is, the adjustment costs of investment are higher than those of employment. However, the costs can also differ between decisions to increase or decrease investment and hiring. While there are search costs and training costs and loss of output when making hires, the job market is more flexible in terminating employment and does not impose such large adjustment costs. Also there is evidence of discrete adjustment that is consistent with fixed adjustment costs (see Varejão and Portugal (2007)) and in this case, discount rate changes would have to be large enough to warrant a change in employment. There is also empirical evidence at the firm level that large temporary uncertainty shocks measured through stock market volatility lead to substantial changes in hiring and investment rates in the short run (Bloom (2009)). Nickell (1986) and Bloom (2009) estimate hiring adjustment costs like recruitment processes, training and redundancy payments to be around 10 to 20 percent of annual wages.

Since the discount rate is undoubtedly correlated with aggregate uncertainty, large discount rate changes may need to be observed in order to trigger investment and employment changes.

Clearly, the adjustment costs of investment and disinvestment can be different because disinvestment costs can be high or some investment could be irreversible which would lead to the scenario that an increase in the discount rate will not necessarily see a decrease in investment. However, it is difficult to test for these effects directly using aggregate data for investment since it is always positive. At the aggregate level investment growth can decrease because there is less investment, depreciation, and disinvestment. We are likely to observe in the aggregate data that firms postpone or cut back on investment, such that the level of investment falls. This is likely to have lower adjustment costs than those adjustment costs associated with increasing investment. We might expect that an increase in the discount rate has a larger effect on reducing investment because at the aggregate level this requires firms simply cutting back on investment which has likely low adjustment costs, as compared to a decrease in the discount rate which should lead to an increase in investment in the short run, but in the presence of adjustment costs. With aggregate employment data the situation is different in that a fall in employment growth is associated with a decrease in the number of people employed and hence is associated with firing.

Given these various adjustment costs and our focus on aggregate data, it might be conceivable that *i*) discount rate variation has a stronger impact on employment than investment decisions, *ii*) firms react stronger to larger changes in the discount rate, and *iii*) firms react differently if those large changes are increases or decreases in the discount rate. We present results consistent with all three predictions. Specifically, we present results that for investment growth, small changes in the discount rate have no forecasting power for investment growth. In contrast, small changes in the discount rate do forecast employment growth in the short run. Why this happens for labour and not investment is probably due to the fact that adjustment costs of labour are smaller than for investment and hence employment reacts to smaller changes in the discount rate than investment because the marginal cost of a new hiring is lower than the marginal cost of a new investment. We also find that a large change in the discount rate does forecast short term investment and employment. Both a fall and a rise in the discount rate forecast employment growth where a rise in the discount rate has a much bigger impact than a fall suggesting the adjustment costs of firing are lower than those of hiring. A rise in the discount rate forecasts a decrease in investment growth whereas a fall in the discount rate has only a small impact on increasing investment growth. This suggests that postponing investment, which is what a fall in the growth rate of investment represents, has lower adjustment cost that increasing investment.

Our paper is clearly related to Lettau and Ludvigson (2002) and Chen and Zhang (2011). However, we make several important contribution over and above these papers. First, Lettau and Ludvigson (2002) only find evidence in support of a long term impact of the discount rate, as measured by the consumption to wealth ratio, *cay*, on investment growth. We show that *cay* is not a stable predictor of stocks returns and hence may not uncover the dynamics between discount rates and investment adequately. Furthermore, Lettau and Ludvigson (2002) ignore how adjustment costs of investment might impact on how the discount rate affects investment.

Chen and Zhang (2011) also find no evidence of a short run effect of the discount rate on employment growth when including macroeconomic controls. Although the dividend price ratio can predict long run employment growth, any additional predictability in the long run as measured by the adjusted $\overline{R}^2$ seems to be driven by overlapping observations.

Chen and Zhang (2011) also ignore the potential for adjustment costs of labor to affect the impact of discount rates on employment decisions.

Overall the extant literature, whilst presenting interesting theoretical insights, has failed to provide empirical support foe these insights. By more accurately measuring discount rate movements and taking adjustment costs into account, our findings present a much richer picture of the role of the discount rate on investment an employment decisions that are consistent with theoretical insights that predict both short term and opposite long term effects of the discount rate on investment and employment growth.

Our paper is also related to Hall (2017) who looks at the role of discount rates on unemployment. The argument here is that a high discount rate will reduce the job value to the owners of the firm through its affect on the present value of productivity. Job value and the present value of wages move together but not in proportion because of sticky wages, so wages fall less than productivity and job value. Therefore, unemployment will increase as firms reduce the workforce when the discount rate increases. Simulations of the model show that an increase in the discount rate has a large immediate impact on unemployment before returning to its normal level. Hall relies on the dividend price ratio to measure discount rates in his model. This leads to a potential weakness in that the dividend price ratio is a weak predictor of the stock market return and hence the discount rate especially at short horizons. Furthermore, Hall's work relies on simulations and does not confront the data on unemployment directly with discount rate movements. But it is interesting to note that Hall's model predicts that an increase in the discount rate today should have an impact on employment in the short run. There are no long run implications of Hall's model. Our paper will focus both on the short run and long run impact of the discount rate.

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 3 presents the data and motivates why cyclical consumption is an appropriate proxy for capturing time-variation in discount rates. Section 4 presents empirical evidence on short-run and long-run predictability of investment and employment growth. Section 5 contains robustness checks. Section 6 concludes.

2 Dynamic Models of Investment and Employment

The single period investment model of Tobin predicts that a decrease (increase) in the discount rate leads to an increase (decrease) in investment. Exactly when in the data this should be observed is uncertain because it depends on whether there is time to build or plan. The problem with Tobin's model is that there appears to be little support for the empirical predictions. Abel and Blanchard (1986) find that it is marginal profitability that drives investment and not the discount rate. This is a puzzling finding since the discount rate is the source of a firm's cost of capital and it would imply that managers do not respond to changes in it. 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, this evidence of the role between discount rates and short term investment is rather indirect. Lettau and Ludvigson (2002) find no evidence that investment growth is predictable by the discount rate at short horizons.

In models of employment growth such a Mortensen and Pissarides (1994) risk premiums and hence the discount rate are constant and consequently there are no implications about the short run or long run predictability of employment growth by the discount rate.

In this section of the paper, we discuss the insights from both Lettau and Ludvigson (2002) and Chen and Zhang (2011) that outline the role that the discount rate can have on future investment and employment decisions in a dynamic setting that includes both the short and long run.

2.1 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 of this 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:

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

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 $\rho_q = 1/\left(1+\exp\left(\overline{m-q}\right)\right)$. 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 $q_t \approx p_t$:

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

where p_t is the current stock prices, 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 $p_t \approx q_t$ where the difference is simply due to the discount rate being 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. Liu, Whited, and Zhang (2009) provide evidence that stock returns are equal to 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:

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

and the dividend price ratio $dp_t \equiv d_t - p_t$ is shown to predict long horizon returns.

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

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

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

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

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 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 (3) a decrease in dp_t predicts a decrease in expected returns (discount rates). From equation (5) this will lead to both the growth rate in q_t and therefore investment to fall over long horizons. That is, future investment growth should have a positive correlation with expected returns. This is the opposite of the one period Q model where a a decline in the discount rate at time time leads to a contemporaneous increase in investment. The ability to predict investment grows with the horizon arises because of the infinite discounted sum of Δq_{t+1+j} on the right hand side of (5).

What should be noted is that a fall in the discount rate today predicts future lower stock returns. In the long run, this fall in stock returns forces prices to fall and subsequently the cost of capital will rise on average. Consequently optimal investment in the future must fall. In sum, 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. Lettau and Ludvigson (2002) find evidence that is consistent with discount rate proxies predicting long run investment growth.

Both Tobin (1969) and Lettau and Ludvigson (2002) assume symmetry in the reaction of investment to a discount rate increase and decrease of the same magnitude. However, this will only be the case if the adjustment costs of investment and disinvestment are the same. When examining aggregate data, we will not observe disinvestment, but rather a reduction in the growth rate of investment which would represent less investment. However, it is not necessarily the case that positive and negative discount rate movements result in the same dynamics for investment growth. For example, the adjustment costs of undertaking new investments are likely to be greater than those of postponing or slowing down the rate of investment. Furthermore, because these costs are likely to be different, it is unlikely that investment growth reacts symmetrically to large and small movements in the discount rate. The reason for this is that when costs are low it is more profitable to change investment quickly, but if these costs are high, firms might wait to investment until a change in the discount rate is large enough to offset the adjustment costs. We investigate these possibilities in the empirical analysis.

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

$$\Delta i_{t+h} = i_{t+h} - i_t = a_0 + a_1 Z_t + v_{t+h} \tag{6}$$

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

2.2 Employment

Chen and Zhang (2011) derive a novel dynamic model of employment growth. The intuition underlying their insight is the same and 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 fall 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 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 zero and one, the stock of employment evolves according to

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

This 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:

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

where X_t is a productivity shock and W_t is the wage rate. Cochrane (1991) outlines conditions for when the return from hiring is equivalent to the stock market return. This requires constant returns to scale (see also Liu, Whited, and Zhang (2009)). So replacing R^H_{t+1} with the stock market return, which embodies the discount rate, provides a number of testable hypothesis 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 first lower employment growth $\left(\frac{N_{t+1}}{N_t}\right)$ and subsequently higher employment growth $\left(\frac{N_{t+2}}{N_{t+1}}\right)$.

Chen and Zhang (2011) identify the dividend price ratio and Lettau and Ludvigson's (2001) *cay*-ratio as good predictors of the equity premium and hence good proxies for the discount rate. The remaining predictor variables, the relative t-bill rate, the term spread and the default spread do not predict the equity premium. Turning to predicting employment growth, the dividend price ratio and *cay* have relatively little predictive power for employment growth (see their Table 3). The relative t-bill rate does predict employment growth in the way implied by the Chen and Zhang (2011) model. However, the long run predictability is weak. The weak evidence of long run predictability is confirmed in multivariate regressions using all predictor variables. Furthermore, when including a set of macroeconomic control variables the short run predictability of employment growth by discount rate proxies disappears altogether and across all horizons there is little evidence that the discount rate predicts employment growth. In sum, variables that predict stock returns do not predict employment growth. There is evidence at short horizons that the relative t-bill rate predicts employment growth. However, no variables predict employment growth after controlling for macroeconomic variables.

The lack of support for Chen and Zhang's (2011) model is not necessarily due to the fact that the discount rate does not predict employment growth in the novel way that they describe. The results could be because of the way they measure the discount rate and the way to look at employment growth dynamics in the face of adjustment costs. Whilst the models of labour dynamics are constructed around a symmetric adjustment costs, it is not necessarily the case that the costs of hiring are the same as the costs of firing. Therefore, it is possible that large or small, or positive or negative, discount rate movements do not result in the same dynamics for employment growth. If the costs of firing are lower than the costs of hiring, then employment growth may react more to a discount rate increase than a similar sized discount rate decrease. Furthermore, because the costs of hiring and firing are likely to be different, it is not necessarily the case that employment growth reacts symmetrically to large and small movements in the discount rate. The reason for this is that in the presence of high adjustment costs employment is only likely to change after relatively large changes in the discount rate. With low adjustment costs, such as firing, employment growth may change after relatively small changes in the discount rate.

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

$$\Delta e_{t+h} = e_{t+h} - e_t = a_0 + a_1 Z_t + u_{t+h} \tag{10}$$

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 u_{t+h} is the error term.

3 Data

Data on investment is private nonresidential investment (seasonally adjusted and inflation adjusted). Data on employment is nonfarm payrolls (seasonally adjusted). We calculate the growth rate of the natural log of investment and employment. All data are sampled quarterly from the first quarter of 1954 to the fourth quarter of 2017.

Following the findings in Atanasov, Møller and Priestley (2020), as the main 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. The data are quarterly, in real per capita terms, and measured in 2009 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 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:

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

Since cc_t is computed based on a 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, Møller, and Priestley (2019) show that a choice of a six-year horizon in the detrending filter is consistent with implications of the Campbell and Cochrane (1999) external habit formation model. Figure 1 shows a time series plot of cc computed from Equation (12) for $k = 24$ along with recession dates as defined by the NBER. The figure illustrates that cc has a clear counter-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, Møller, and Priestley (2019) 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 also consider other predictors of aggregate stock returns which have been used previously to predict investment growth and employment growth in Chen and Zhang (2011) and Lettau and Ludvigson (2002). 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 Treasury bill rate; the default yield spread (dfy) which is the difference between the BAA- and AAA-rated corporate bond yields; 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)); and the relative rate ($rrel$) which is three month t-bill rate minus its one-year moving average.

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 the growth rate in after tax profits; growth in average Q (Dq) as constructed in Bernanke, Bohn, and Reiss (1988); and the GDP growth rate ($Dgdp$). Data on these variables are available from the FRED database of the St. Louis Federal Reserve Bank.

3.1 Predicting Stock Returns

Which variables are good proxies for the discount rate? To answer this, we need to consider 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 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 β, we use heteroskedasticity and autocorrelation robust t-statistics of Newey and West (1987) with h lags.

Panel A of 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 falls. In bad times when consumption falls relative to its trend the discount rate rises. 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 6 percentage points at an annual rate. This 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 over 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 estimated coefficients are statistically significant at all horizons with the $\bar{R}^2$ rising to 0.44 at the twenty quarter horizon.[2] These findings confirm those in Atanasov, Møller, and Priestley (2019) that cc is a very good predictor of aggregate stock returns and hence an excellent candidate to track discount rate movements.

The remainder of Table 1 reports univariate stock return predictability regressions using the other predictor variables. The dividend price ratio, the default spread, and $rrel$ struggle to predict stock returns at any horizon 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 forecast 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. For example, at the four quarter horizon the $\bar{R}^2$ is 0.13 when predicting returns with cc and only 0.05 with tms. These differences continue right to the twenty quarter horizon where the $\bar{R}^2$ is 0.44 when predicting returns with cc and 0.17 with tms. Finally, cay has predictive power for returns at all horizons, but to a much lower extent than cc when comparing $\overline{R}^2$s. From the perspective of these univariate regressions, there is strong evidence to suggest that cc is a much better proxy for discount rate movements than previously used predictor variables.

Panel B reports a multivariate regression of returns on all of the predictor variables. Only cc and cay retain statistical significance with the extent of the statistical significance falling at shorter horizons for cay. Therefore, it seems that both cc and cay might act as proxies for the discount rate. Before we conclude on this issue it is important to ascertain if the predictor variables have stable predictive power over the sample period.

[2]The coefficient estimates remain statistically significant when bootstrapping the standard errors.

We show in Table 2 that *cc* is the only predictor variable that has the ability to predict stock returns consistently and strongly in two equal sub-samples. Panel A of Table 2 shows the results when predicting stock returns for the early sample period from 1954Q1 to 1984Q4. *cc* can predict returns at all horizons with similar statistical and economic significance as in the full sample in Table 1. The same cannot be said of other predictor variables. For example, the dividend price ratio can predict stock returns in this early sample at short horizons, whereas in the full sample it could not predict returns at any horizon. The term spread can predict only at the one and two quarter horizons in this early sample, the opposite of the full sample. The default spread has no predictive ability in this early sample, as in the full sample. The relative interest rate has predictive ability at horizons of a year and less in the early sample, whereas in the full sample there is only weak evidence of predictive ability at the longest horizons. *cay* has strong predictive ability at all horizons for this early sample, as in the full sample.

Panel B of Table 2 reports results for the later sample of 1985Q1 to 2017Q4. *cc* retains its strong statistical and economic ability to predict returns at all horizons. Thus, *cc*'s ability to predict returns is inherently strong and stable through the two sub-periods and the full sample. This is the only predictor variable that can make this claim. For example, the dividend price ratio can predict returns in the later sample although, as opposed to the early sample, the predictability now is stronger at longer horizons. Even though there is some evidence of return predictability by the dividend price ratio it is not consistent across horizons in these two samples, and it is not consistent with the evidence from the full sample that the dividend price ratio cannot predict stock returns. The term structure can predict returns at the one and two quarter horizon in the early sub-sample, the opposite is true in the later sample where it can predict returns only at longer horizons. The default spread has no predictive ability in the later sample, consistent with the early sample and the full sample. Whilst the relative interest rate could predict stock returns at horizons of one year and less in the early sample, it has no predictive ability in the later sample. Finally, we find no ability of *cay* to predict returns in the later sample, in contrast to the early sample. So, although *cay* can predict stock returns over the full sample period, this seems to be driven by the strong predictability *cay* has in the early sample because it is not able to predict returns in the later sample.[3]

In sum, *cc* is the only variable that has the ability to predict stock returns in a consistent and strong way over the full sample and two sub-samples. Therefore, it is the

[3] We have tried estimating the cointegrating regression for *cay* separately for the two sub-samples, but this does not lead to any noticeable differences in the results.

most appropriate proxy for the discount rate to consider when examining investment and employment growth predictability. Using cc as a proxy for discount rate movements in predicting investment and employment growth could provide new insights into investment and employment growth dynamics.

There is a further advantage to using cc in investment and employment growth regressions in that we know that extant predictor variables are in many cases only able to predict stock returns in bad times when the discount rate increases by large amounts, often defined as economic recessions (see, for example, Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018)). This means that they are unable to say anything about discount rates outside of the very short periods of recessions. This is important since, as measured by the NBER recession dating methodology, over the sample period used here, recessions constitute only 40 out of 255 quarters, less than 20% of the sample period. Atanasov, Møller, and Priestley (2019) show that this is not the case for cc which can predict stock returns when discount rates rise (bad times) and fall (good times).

The ability of the discount rate proxy to predict returns in both good and bad times could be particularly important for investment and employment growth predictability since a fall in the discount rate in good times will constitute an important signal to increase investment and employment in the short term and decrease them in the long term. This cannot be captured with stock return predictor variables that have been used in the extant literature because they cannot predict a fall in returns in good times and hence a fall in the discount rate. In contrast, cc can predict stock returns in good and bad times. Thus using cc in predicting employment and investment growth regressions could provide new insights into the role of the discount rate in investment and employment decisions.

4 Investment and Employment Growth Predictability

The main empirical results that we report focus on the role of cc in predicting investment and employment growth. The reason for this is that cc is the only variable that has a stable role in predicting aggregate stock returns and hence is a good proxy for discount rate fluctuations. Recall that in the short run a fall (rise) in the discount rate should predict an increase (decrease) in both investment and employment growth. In the long run a fall (rise) in the discount should predict a decrease (increase) in investment and employment growth. Therefore, we should expect a positive coefficient on cc in the short run because an increase in cc reflects good economic times with lower discount rates and hence higher investment. In contrast, theory predicts we would expect to see a negative coefficient estimate when we regress long horizon investment growth on cc.

Table 3 reports the results of investment growth predictability by cc and shows that the estimated coefficients are negative at all horizons. However, the coefficients are not statistically significant until the fourth quarter. The coefficient estimate at the four quarters horizon is statistically significant but cc only has a minor impact with an $\overline{R}^2$ of 0.04. However, at horizons of eight quarters and longer the estimated coefficients are highly statistically significant and the $\overline{R}^2$ ranges from 0.12 at the eight quarter horizon to 0.32 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. 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 4.1%, leads to a change in investment, based on the eight quarter horizon estimate of 1.7% per annum. This is a substantial amount compared on the mean growth rate of investment of 4% per annum.

The results confirm that there is a strong support for the long run implications of the dynamic model of investment. However, at short horizons, the estimated coefficient has the wrong sign and, hence, we do not see an immediate or short run increase (decrease) in investment given a decrease (increase) in the discount rate. Therefore, the short run implication of the investment model is rejected.

Table 4 examines employment growth predictability. As in the case of investment growth predictability, we find negative coefficient estimates at all horizons although the estimates are very small and are not statistically significant at the one, two or four quarter horizons. However, like in the case of investment growth, the economic impact of cc starts at the eighth quarter. We find that whilst there are no short term effects, there are statistically significant and economically large longer horizon effects at eight or more quarters. The $\overline{R}^2$ increases from 0.08 at the eight quarter horizon to 0.25 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 to this by 0.5% per annum, which is a quarter of the mean annual growth rate of 2%.

In summary, using cc to proxy discount rate movements uncovers strong support for the long run implications of investment and employment growth and this is stronger than the evidence provided in the extant literature. However, consistent with the extant literature, there is no evidence to support the short run predictions of the models.

4.1 Short and Long Run Dynamics

So far, we have found strong support for the long run predictions of the dynamic models of both investment and employment growth. However, we have not found evidence to support the short run predictions of the models of investment and employment that a fall (rise) in the discount rate leads to an initial short run increase (fall) in investment or employment. One potential reason for this is that the level of cc is a good indication of the direction of discount rates over longer horizons, but it might be less useful in capturing the short run relation between the discount rate and the growth rates of investment and employment. For example, the level of cc today may be high and a decrease in cc in the next period is an indication of a rise in the discount rate, however, the level of cc is still relatively high. It might be more appropriate to use the change in cc to measure the immediate direction of the discount rate. In light of this, we examine whether the change in cc can predict investment and employment growth in the short run. Later, we also derive news about discount rates from the Campbell (1991) decomposition of unexpected returns and find very similar results.

In Table 5, we report the results from regressing investment growth on the change in cc. Just as the investment model predicts, we find that an increase (decrease) in cc, which is consistent with a lower (higher) discount rate, predicts an increase (decrease) in investment at short horizons. The estimated coefficients are statistically significant from one quarter to the four quarter horizon, suggesting that firms increase investment given news of a fall in the discount rate. At the one quarter horizon a one standard deviation movement in the change in cc, which is 1%, leads to a 2% change in investment growth. As predicted by the dynamic model of investment behavior, the impact of a change in the discount rate does not last long. For example at the eight quarter horizon, the coefficient estimates are only marginally significant and the $\overline{R}^2$ falls to 0.02. At longer horizons the estimate approaches zero and the $\overline{R}^2$ turns negative.

In the lower part of Table 5, we predict investment growth with both the change in cc and its level. These predictive regressions should capture both short run and long run dynamics of investment growth in response to the discount rate. We find that a fall (rise) in the discount rate does increase (decrease) investment but only in the short run. At the same time, the level of the discount rate does predict a fall in long run investment to the same extent as it did when we only included the level of cc in the regressions. Accordingly, this is the first paper that fully confirms the impact of discount rates on investment growth in the short and long run in a way that is consistent with theoretical models of dynamic investment behavior. At the one quarter horizon, the $\overline{R}^2$ is 0.05 and rises to 0.33 at the twenty quarter horizon. Including the change in the discount rate does not affect the long run predictability of investment growth, but it does capture the dynamics of investment growth in the short run, as well as the long run, in a way that is consistent with the dynamic model of investment growth with capital adjustment costs.

Turning to the role of changes in the discount rate and its impact on employment growth predictability in Table 6, we find a similar pattern to that of the dynamics for investment growth when using the change in cc. At short horizons, we find that a fall (rise) in the discount rate leads to an increase (decrease) in employment growth at the one quarter to four quarter horizon and the slope coefficient drops substantially at the eight quarter horizon and it is not statistically significant at all after eight quarters. It is interesting to note that the effect on employment growth as measured by the $\overline{R}^2$ is strongest at the two quarter horizon and the predictability of employment growth is stronger at the short horizon than that of investment growth. For example, the $\overline{R}^2s$ are 0.12 and 0.11 at the one and two quarter horizons when predicting employment growth and 0.05 and 0.07 for investment growth. The economic impact is substantial as a one standard deviation movement in the change in cc leads to a movement in employment growth of 0.9%, recall that the mean employment growth rate is 1.7% per annum. The larger impact the change in cc has on employment growth compared to investment growth could imply that the adjustment costs of employment are lower than those on investment and this is what leads to a bigger short run impact of a change in the discount rate on employment as compared to investment.

The lower part of Table 6 also includes the level of cc along with the change in cc. In this case, we still find that the change in the discount rate can predict short run employment growth in that a decrease (increase) in cc, which is indicative of an increase (decrease) in the discount rate, predicts lower employment in the short run. We also find that in the long run employment growth decreases (increases) when the discount rate falls (rises) just as in Table 4 when only including cc. As in the case of investment growth, we observe that employment growth reacts to the discount rate as the dynamic model of Chen and Zhang (2011) predicts. The extent of predictability at longer horizons is comparable between investment growth and employment growth but there is more predictability of employment growth at shorter horizons suggesting that adjustment costs of labour are smaller than those of investment.

4.2 The Size of Discount Rate Shocks

It may be possible to get a better indication of the role of the discount rate in the determination of investment and employment growth if we look at large relative to small changes in the discount rate. The reason for this is that in the presence of adjustment costs it may require the discount rate to rise or fall by a large amount for firms to find it profitable to make changes to investment and employment levels. Furthermore, looking at how investment and employment growth changes when discount rate changes are small and large might shed further light on the relative size of investment and employment adjustment costs. That is, can we say something more about whether employment adjustment costs are different to investment adjustment costs? In light of these possibilities, we need to modify the predictive regressions.

Table 7 reports the results of regressing investment growth onto discount rate changes when decomposing the discount rate into large changes, defined as those changes that are greater than a one standard deviation change in cc in an absolute sense, and small changes which are those less than a one standard deviation change in cc. Large changes in the discount rate have a statistically significant estimated coefficient over the one to the four quarter horizons. They also have a much larger impact on investment growth than small changes which never have a statistically significant estimated coefficient. The lower part of Table 7 shows that the inclusion of the level of cc confirms the long run relation between investment growth and the discount rate. Note that the inclusion of the level of cc has no effect on the short run dynamics captured by the change in cc for both large and small changes. The finding that a discount rate change has to be large to lead to a change in investment growth suggests that there are reasonably sized adjustment costs of investment that prevent firms from investing when discount rates change by less than one standard deviation from their mean.

Table 8 reports the results for regressing employment growth on to large and small discount rate changes. We also find that large changes in the discount rate have substantial forecasting power for one to four quarters and marginally so at eight quarters. Small changes in the discount rate also have a statistically significant coefficient estimate at the one quarter horizon and marginally so at other short horizons. The estimated coefficients on the small change in cc are smaller than the estimated coefficients on large changes in cc. Similar to the case of investment growth, the lower part of Table 8 shows that the results are unaffected by the inclusion of the level of *cc*.

The findings regarding the size of the change in the discount rate suggest that the adjustment costs of investment are larger than those of employment because employment is affected by small changes in the discount rate whereas investment is not. It appears that firms are more likely to adjust employment levels rather than investment levels when discount rates changes are small.

4.3 Direction and Magnitude of Changes in the Discount Rate

We now consider the possibility that adjustment costs of investment could be different from those of disinvestment and, similarly, the adjustment costs of hiring and firing could be different. Dealing with aggregate investment data makes the interpretation of adjustment costs different than if we were analyzing data at a firm or plant level. For example, at the plant level the adjustment costs of disinvestment can be high due to dismantling costs or fire sales and some investment could be irreversible. This would imply high costs of disinvestment. However, with aggregate data we do not observe disinvestment, but rather a reduction in the level of investment. The reduction in investment which could involve postponing and cancelling planned investment is likely to involve lower adjustment costs than those of increasing investment. With employment the situation is different in that a fall in employment growth is associated with a decrease in the number of people employed and hence is associated with firing.

Given the use of aggregate level investment data, we might expect that an increase in the discount rate has a larger effect on investment than a decrease in the discount rate because at the aggregate level this requires firms simply cutting back on investment which has no adjustment costs, as compared to a decrease in the discount rate which should lead to an increase in investment in the short run, but in the presence of adjustment costs. Therefore, we now attempt to interpret how positive and negative changes in the discount rate might affect investment growth. Panel A of Table 9 reports the results with just the positive and negative changes in the discount rate and Panel B repeats this but conditions on including the level of the discount rate. In Panel A, we see that a fall in *cc*, indicating an increase in the discount rate, has a much larger impact on investment growth than an increase in *cc* which represents a fall in the discount rate. The impact of an increase in the discount rate as measured by the size of the coefficient estimate is more than double that of the impact of a change in the discount rate recorded in Table 5 when we do not split the discount rate into positive and negative changes in the discount rate.

At the one quarter horizon the $\overline{R}^2$ is also somewhat larger in Table 9 at 0.08 as opposed to 0.05 in Table 5. Thus, we observe a strong reaction on investment activity from a large increase in the discount rate where managers cut back on, or postpone investment.

In contrast, in the last three rows of Panel A in Table 9, we see that an increase in cc indicating a fall in the discount rate does not lead to a strong short run increase in investment. The coefficient estimates and $\overline{R}^2$s are smaller than when the discount rate rises and the estimates do not become statistically significant until the second quarter and only marginally so at the fourth quarter horizon. This suggests the time to build/plan in increasing investment is longer than in decreasing the level of investment. This makes sense since there is less planning and building involved in postponing or reducing investment. Panel B confirms that these short run effects of the discount rate change are unaffected when including the level of the discount rate, and we still find the same role for the level of cc in predicting long run investment growth.

With respect to employment, it is plausible that adjustment costs of firing are lower than those of hiring since the latter does not require training or disruption to output. In this case, we would expect an increase in the discount rate to have a larger impact on decreasing employment than a decrease in the discount rate would have on increasing employment, since the later involves higher adjustment costs.

Table 10 reports results from regressing employment growth on positive and negative changes in cc. We observe that both positive and negative changes in cc affect employment growth and the effects are highly statistically significant and economically large. However, there is a substantial difference between the size of the estimated coefficient as well as the size of the $\overline{R}^2$ when we consider negative and positive changes which is consistent with higher adjustment costs of hiring. A decrease in cc, which is the equivalent of an increase in the discount rate, leads to a fall in employment growth that is statistically significant from the first to the eighth quarter, although at the eighth quarter the impact is much less as measured by the $\overline{R}^2$. The coefficient estimates rise from 0.36 at the one quarter horizon to 1.03 at the four quarter horizon. The impact of the discount rate as measured by the $\overline{R}^2$ is decreasing from the first quarter from 0.15 to 0.05 at the eighth quarter. Employment growth falls quickly in response to an increase in the discount rate in that the effect is felt in the first four quarters most strongly.

We find a similar pattern when the discount rate falls are measured by an increase in cc but the estimated coefficient is almost half the size of that when the discount rate increases and the $\overline{R}^2$ is more than three times smaller and only statistically significant at the one to four quarter horizons. These patterns in the estimated coefficients and the $\overline{R}^2$s suggest that the adjustment cost of firing are lower than those of hiring since employment growth reacts more to an increase in the discount rate. Panel B of Table 10 confirms that these short run effects of the discount change rate are unaffected when including the level of the discount rate, and we still find the same role of the level of *cc* in predicting long run employment growth.

4.4 Discount Rate News and Cash Flow News

The analysis so far has focused on regressions that predict investment and employment growth with proxies for the discount rate. We have shown that changes in the discount rate, as proxied by *cc*, do capture movements in investment and employment growth which are in line with the theoretical models of investment and employment discussed earlier. In this part of the paper, we investigate other established ways to generate news about discount rates that might also provide information regarding the short term impact of discount rates on investment and employment growth.

We use the Campbell and Shiller (1988) log linearization of stock returns to decompose stock returns into news about future discount rates and news about future cash flows. This methodology provides us with a measure of discount rate news that firms should react to in the short term. This methodology also has the further advantage of providing cash flow news which is a proxy of future profitability which also can be a source of investment growth fluctuations given in equation (1). Therefore, we can compare the role of discount rate and cash flow shocks directly on investment and employment decisions.

Consider Campbell's (1991) decomposition of unexpected returns from the present value model (see Campbell and Vuolteenaho (2004) also):

$$\begin{aligned} r_{t+1} - E_t(r_{t+1}) &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^i \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho^i r_{t+1+i} \\ &= N_{CF,t+1} - N_{DR,t+1} \end{aligned} \tag{14}$$

where r_{t+1} is the log return on the aggregate stock market, d is log dividends, ρ is the discount factor, and N_{CF} and N_{DR} are news about future dividend growth (cash flows) and future returns (discount rates), respectively. Following Campbell (1991), a VAR can be used to obtain $E_t(r_{t+1})$ and $(E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho^i r_{t+1+i}$. These are plugged into equation (14), which can then be solved for $(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^i \Delta d_{t+1+j}$. Assuming the data are generated by a first order VAR:

$$\mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{u}_t \tag{15}$$

then Campbell and Vuolteenaho (2004) show that the news terms are given by

$$\begin{aligned} N_{CF,t} &= (\mathbf{e}_1' + \mathbf{e}_1'\boldsymbol{\lambda})\mathbf{u}_t \\ N_{DR,t} &= \mathbf{e}_1'\boldsymbol{\lambda}\mathbf{u}_t \end{aligned} \tag{16}$$

where $\mathbf{e}_1$ is a vector that picks out the first element from $\mathbf{z}_t$, which is returns in Campbell and Vuolteenaho (2004), and $\boldsymbol{\lambda} = \rho\mathbf{A}(\mathbf{I} - \rho\mathbf{A})^{-1}$.

The estimation of the news terms requires that we specify a VAR that includes variables that predict stock returns. We set $\mathbf{z}_t' = [r_t \quad dp_t \quad cc_t]$ where the dividend price ratio, dp, is included following Engsted, Pedersen, and Tanggaard (2012) who show that it is necessary for the VAR to be valid. Once the VAR is estimated, we construct $N_{DR,t} = \mathbf{e}_1'\boldsymbol{\lambda}\mathbf{u}_t$ and $N_{CF,t} = (\mathbf{e}_1' + \mathbf{e}_1'\boldsymbol{\lambda})\mathbf{u}_t$.

We can use standard predictive regressions of investment and employment growth:

$$\Delta x_{t+h} = a_0 + a_1 N_{DR,t} + a_2 N_{CF,t} + v_{t+h} \tag{17}$$

where Δx_{t+h} is either investment or employment growth. Table 11 reports the results for predicting investment growth with discount rate news and cash flow news. Regarding the impact of discount rate news, we find very similar evidence as that when we used the change in cc. There is a marginally statistically significant estimate at the one quarter horizon with a coefficient estimate of -0.101, confirming that news regarding an increase (decrease) in the discount rate reduces (raises) investment. At the second and fourth quarters both the statistical significance and the economic significance of the estimated coefficients increase somewhat. The coefficient estimates are -0.243 and -0.431 at these two horizons. At longer horizons, news about discount rates has no statistical or economic effect. These findings support our earlier results that use the change in cc to proxy the discount rate and the predictions of models of investment that an increase (decrease) in the discount rate news reduces (increases) investment in the short run.

We also see that the news about future cash flows, or profitability, does have an impact at short horizons in that news about an increase (decrease) in cash flows raises (lowers) investment. Like the case for discount rate news, news about cash flows has its strongest impact on investment at the second and fourth quarters and there is also some evidence of predictability at the eighth quarter, although this is much weaker than at the fourth quarter. At longer horizons the coefficient estimates are not statistically significant and the $\overline{R}^2$ is zero.

Both news about cash flows and discount rates have a short run impact on investment growth. We can try and assess which of the two news terms is the most important. For example, based on the estimate at the second quarter horizon, a one standard deviation movement in the discount rate news is 0.03 per quarter and leads to a change in investment growth of just under 2% on an annual basis. This is large economically given that the mean annual growth rate of investment is a little over 4%. It is also very close to the impact that we measured when using the change in cc to capture short run effects. A one standard deviation movement in the cash flow news which is 0.06 leads to around a 1% change in investment growth on an annual basis. Thus, news about discount rates has a larger impact on investment growth than news about cash flows.

Table 12 reports the impact of discount rate news and cash flows news on employment growth. News regarding an increase (decrease) in the discount rate reduces (raises) employment growth. The coefficient estimates are statistically significant from the one quarter horizon to the eight quarter horizon, although at the eight quarter horizon the statistical significance falls as does the $\overline{R}^2$. A one standard deviation movement in discount rate news results in a 0.7% per annum movement in employment growth which is substantial given that the mean growth rate of employment is around 1.7% per annum and reassuringly similar to the value found when using the change in cc to proxy the discount rate. There is no strong evidence that news about cash flows predicts employment growth at any horizon.

The results from using a VAR to generate discount rate news and cash flow news provide a novel way to look at the issue of whether movements in discount rates and cash flows (profitability) lead to changes in investment and employment. This alternative methodology allows us to confirm earlier results based on the change in cc that the discount rate predicts both investment growth and employment growth in the short run in the manner predicted by theoretical models. We also find evidence of cash flows news predicting investment growth in the short run as predicted by standard investment models. Overall, discount rates tend to be important in determining movements in the short run of both investment and employment growth, a novel result in the literature.

5 Robustness

In this section, we undertake some robustness tests. We first control the predictive regressions for a set of macroeconomic variables that are unrelated to the discount rate. The second set of robustness tests examines alternative proxies for the discount rate. Finally, we analyze whether our results are robust to alternative ways of detrending consumption.

5.1 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)). Following this literature, we consider the following: 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 the growth rate in average Q, *dq*; and the first lag of the growth rate in either investment or employment, *di* or *de*. We aim to establish if the importance of discount rates that we have uncovered so far remains after controlling for these macroeconomic variables.

Panel A of Table 13 reports the results of predicting investment growth with the lagged level and change in *cc* and the four macroeconomic variables. From the table, we see that the level of *cc* remains strongly statistically significant in predicting investment growth across all horizons. In addition, the change in *cc* continues to be statistically at the 10% level for the two-quarter horizon and at the 5% level for the four-quarter horizon. Panel B of Table 13 reports the results of predicting employment growth with the lagged level and change in *cc* and the four macroeconomic variables. We again observe that the level of *cc* remains strongly statistically significant across all horizons and the change in *cc* is now statistically at horizons up to eight quarters. We thereby confirm that our findings regarding the role of the discount rate in investment and employment growth are robust to the inclusion of macroeconomic controls.

5.2 Other Discount Rate Proxies

Both Lettau and Ludvigson (2002) and Chen and Zhang (2011) use the same set of variables that have been used to predict stock returns to predict investment and employment growth respectively. These are the log dividend-price ratio (*dp*), the term spread

(tms), the default yield spread (dfy), the consumption-wealth ratio (cay) of Lettau and Ludvigson (2001), and the relative t-bill rate ($rrel$).

Panel A of Table 14 reports the results of predicting investment growth with cc and the five other predictor variables. We find that the dividend-price ratio cannot predict investment growth over this sample period, mirroring its lack of predictability for stock returns. Higher values of $rrel$ predicts higher investment in the short run but the coefficient estimates turn negative at horizons of and over eight quarters, and they are not statistically significant. We find similar results as Lettau and Ludvigson (2002) for tms and def in that the former can predict investment growth at long horizons, but with the wrong sign, and the later at short horizons, but with the wrong sign. In this multivariate regression using all the predictor variables, cc retains it predictive power at long horizons. The $\overline{R}^2$ at the twenty quarter horizon is 0.37, which is just a small amount larger than the $\overline{R}^2$ when using cc alone suggesting that other variables add little in terms of predicting investment. In this sample period, we also find that cay has no predictive power for investment growth.

Panel B of Table 14 reports the results of predicting employment growth with cc and the five other 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. While the dividend-price ratio has weak predictive power for investment growth, it has significant predictive power for employment growth. The term spread also has significant predictive power for employment growth, but it predicts with the wrong sign. The default spread predicts employment growth with significantly negative coefficients at horizons up to three years, but this predictive power does not seem to have any relation to time-varying discount rates given that def does not have a significant relation to future stock returns. The relative short rate has significant predictive power only at very short horizons and, finally, cay does not appear to be a strong predictor of employment growth in our sample.

Overall, we find that cc contains significant predictive power for both stock returns, investment growth, and employment growth, while other proxies for discount rates often fail to contain significant predictive power or predict with the wrong sign according to the dynamic models.

5.3 Alternative Ways of Detrending Consumption

We use the Hamilton (2017) 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. To check the robustness towards detrending techniques, we consider a quadratic trend model:

$$c_t = \beta_1 + \beta_2 t + \beta_3 t^2 + \omega_t, \tag{18}$$

where cyclical consumption is then given by the residual from the quadratic equation. We also consider the case where consumption follows a random walk, which means that cyclical consumption is defined as $cc_t = c_t - c_{t-k}$ with $k = 6$ years as in the above. Table 15 shows predictability results when using these two alternative ways of detrending consumption. We see that both measures are statistically significant in predicting stock returns, investment growth and employment growth and that the degree of predictive power is similar to that obtained using the Hamilton (2017) regression filter in equation (11). In some cases, the quadratic trend model generates somewhat higher R^2 statistics and in that sense the Hamilton detrending procedure provides a conservative view of the degree of predictability.

6 Conclusion

Dynamic models of employment and investment growth imply that discount rate variation should affect both short-run and long-run fluctuations in employment and real investment spending. However, 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, Martin and Nardari (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, Møller, and Priestley (2019)).

It is important to be able to track the discount rate when it decreases as well as when it increases because both investment and employment models predict movements in investment and employment growth when the discount rate increases (bad times) and when the discount rate decreases (good times). This is a crucial issue because firms' investment and employment decisions are unlikely to be symmetric around discount rate increases and decreases due to asymmetries in the adjustment costs when firms increase investment and employment compared to when firms decrease investment and employment. Furthermore, these asymmetries in adjustment costs and the difference in investment as compared to employment adjustment costs are likely to mean that the size and the sign of the discount rate movement might be important in determining investment and employment decisions. This paper is the first to address all these issues.

The use of a successful, theoretically underpinned proxy for a time-varying discount rate allows us to connect both short-run and long-run fluctuations in employment and investment to a time-varying discount rate. We show that a current fall in the discount rate predicts an increase in short-run investment and employment, while long-run investment and employment decreases, which is consistent with the implications of dynamic labor market and investment models. We thereby confirm the prediction of an opposite impact of the discount rate on employment and investment at short and long horizons. Furthermore, we show that differences in adjustment costs of investment and employment lead to differences in how firms react to whether the discount rate increases or decreases. A key result is that an increase in the discount rates, which typically happens during recessions, has a stronger effect on employment and investment than a decrease in the discount rate. Overall, our findings suggest that a time-varying discount rate can have a substantial impact on business cycle fluctuations at both short and long horizons through managers' decisions regarding investment and employment.

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Table 1. Predicting Discount Rates

Panel A presents results of univariate 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 (def), the relative interest rate ($rrel$), and the consumption-wealth ratio (cay). Panel B reports results from multivariate regressions where all predictive variables are included. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Univariate Regressions

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.375	-0.740	-1.434	-2.543	-3.316	-4.427	-5.286
t-stat	-3.189	-3.626	-3.885	-4.153	-4.615	-5.686	-6.128
$\overline{R}^2$	0.034	0.063	0.126	0.223	0.292	0.412	0.437
dp	0.019	0.042	0.078	0.128	0.150	0.179	0.243
t-stat	1.424	1.596	1.586	1.432	1.335	1.489	2.157
$\overline{R}^2$	0.005	0.016	0.031	0.047	0.049	0.056	0.083
tms	0.657	1.270	2.586	4.564	6.683	8.324	9.288
t-stat	1.693	1.814	2.419	3.719	4.645	3.769	2.694
$\overline{R}^2$	0.010	0.020	0.047	0.084	0.140	0.174	0.168
def	0.611	2.055	3.602	4.861	5.788	10.307	18.643
t-stat	0.399	0.863	1.051	1.026	0.961	1.359	2.126
$\overline{R}^2$	-0.003	0.002	0.006	0.006	0.006	0.022	0.064
$rrel$	-0.819	-1.353	-2.096	-2.034	-2.548	-3.429	-4.850
t-stat	-1.724	-1.520	-1.194	-1.448	-1.997	-2.127	-2.527
$\overline{R}^2$	0.010	0.014	0.018	0.007	0.010	0.016	0.027
cay	0.631	1.266	2.561	4.992	6.751	8.044	8.681
t-stat	2.601	2.709	2.932	3.901	4.768	5.263	5.407
$\overline{R}^2$	0.020	0.039	0.086	0.179	0.241	0.268	0.245

Panel B: Multivariate regressions

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.288	-0.550	-1.027	-1.797	-2.259	-3.258	-3.885
t-stat	-2.054	-2.454	-2.864	-2.939	-3.062	-4.641	-5.337
dp	0.010	0.021	0.043	0.073	0.098	0.075	0.076
t-stat	0.644	0.742	0.799	0.791	0.994	0.738	0.724
$term$	0.052	0.233	0.986	2.608	4.471	4.633	4.435
t-stat	0.098	0.268	0.716	1.121	2.141	2.137	1.527
def	-0.545	0.162	0.416	0.815	0.039	4.225	11.484
t-stat	-0.348	0.068	0.119	0.206	0.010	1.036	2.116
$rrel$	-0.726	-0.921	-0.912	0.652	1.498	1.733	1.423
t-stat	-1.309	-1.013	-0.488	0.327	0.980	0.916	0.659
cay	0.485	0.989	1.980	3.901	5.102	5.839	6.138
t-stat	1.877	2.113	2.354	2.975	3.711	4.187	4.262
$\overline{R}^2$	0.042	0.088	0.191	0.364	0.496	0.617	0.631

Table 2. Stability

The table reports results of univariate 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. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. Panel A reports results for the period 1954Q1 to 1984Q4 and Panel B reports results for the period 1985Q1 to 2017Q4.

Panel A: 1954Q1 to 1984Q4							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.496	-0.911	-1.617	-2.289	-2.413	-3.436	-4.439
t-stat	-2.444	-2.640	-2.527	-2.533	-3.218	-4.697	-5.296
$\overline{R}^2$	0.051	0.077	0.133	0.188	0.221	0.419	0.474
dp	0.072	0.164	0.305	0.429	0.383	0.372	0.629
t-stat	2.180	2.565	2.928	2.280	1.760	1.563	2.152
$\overline{R}^2$	0.030	0.078	0.147	0.203	0.148	0.112	0.200
tms	1.517	2.436	3.519	1.094	0.583	0.956	4.368
t-stat	2.764	2.267	1.738	0.619	0.255	0.438	0.963
$\overline{R}^2$	0.052	0.058	0.060	-0.004	-0.008	-0.007	0.019
def	1.329	2.525	2.726	0.287	-6.675	-11.818	-10.878
t-stat	0.749	0.790	0.574	0.063	-1.379	-1.305	-0.901
$\overline{R}^2$	-0.001	0.003	-0.002	-0.009	0.011	0.034	0.008
$rrel$	-1.548	-2.684	-4.542	-2.898	-1.844	-1.084	-4.603
t-stat	-2.797	-2.968	-2.492	-1.695	-1.251	-0.483	-1.570
$\overline{R}^2$	0.065	0.087	0.134	0.031	0.005	-0.006	0.019
cay	0.916	1.790	3.331	5.677	6.726	8.598	10.098
t-stat	2.601	2.333	2.236	3.366	5.268	7.330	7.433
$\overline{R}^2$	0.038	0.067	0.123	0.244	0.371	0.558	0.517

Panel B: 1985Q1 to 2017Q4							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.370	-0.783	-1.653	-3.426	-4.800	-6.237	-7.130
t-stat	-2.665	-2.691	-2.858	-3.206	-3.961	-5.899	-11.359
$\overline{R}^2$	0.027	0.067	0.160	0.328	0.439	0.577	0.605
dp	0.043	0.083	0.153	0.262	0.341	0.387	0.426
t-stat	2.101	2.421	2.434	2.278	2.657	2.830	2.947
$\overline{R}^2$	0.024	0.052	0.103	0.160	0.220	0.248	0.281
tms	-0.133	0.225	1.936	7.783	10.955	11.704	9.360
t-stat	-0.211	0.202	1.171	2.342	2.989	3.690	2.310
$\overline{R}^2$	-0.007	-0.007	0.014	0.159	0.221	0.231	0.155
def	-0.578	1.185	4.402	9.533	10.891	15.023	21.421
t-stat	-0.219	0.338	0.985	1.145	1.102	1.239	1.545
$\overline{R}^2$	-0.007	-0.006	0.004	0.019	0.023	0.043	0.087
$rrel$	1.029	2.002	4.107	1.057	-1.165	-3.368	-3.184
t-stat	1.223	1.201	1.241	0.385	-0.285	-0.893	-1.284
$\overline{R}^2$	0.005	0.015	0.042	-0.006	-0.006	0.006	0.007
cay	0.361	0.781	1.868	4.569	6.529	6.659	5.474
t-stat	1.228	1.427	1.728	1.787	1.749	1.471	1.305
$\overline{R}^2$	-0.001	0.008	0.036	0.104	0.124	0.090	0.049

Table 3. Investment Predictability

The table presents results of predictive regressions, $\Delta i_{t+h} = i_{t+h} - i_t = a_0 + a_1 cc_t + v_{t+h}$, where $\Delta i_{t+h} = i_{t+h} - i_t$ is h-period ahead log growth in investment and cc_t is cyclical consumption. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.036	-0.104	-0.329	-0.858	-1.248	-1.520	-1.896
t-stat	-1.083	-1.476	-2.472	-3.259	-3.017	-2.896	-3.388
$\overline{R}^2$	0.001	0.009	0.039	0.121	0.190	0.239	0.318

Table 4. Employment Predictability

The table presents results of predictive regressions, $\Delta e_{t+h} = e_{t+h} - e_t = a_0 + a_1 cc_t + u_{t+h}$, where $\Delta e_{t+h} = e_{t+h} - e_t$ is h-period ahead log growth in employment and cc_t is cyclical consumption. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.001	-0.016	-0.073	-0.226	-0.363	-0.490	-0.643
t-stat	-0.074	-0.746	-1.722	-2.473	-2.446	-2.378	-2.493
$\overline{R}^2$	-0.004	-0.001	0.020	0.082	0.138	0.186	0.246

Table 5. Investment Predictability: Change in the Discount Rate

The table presents results of predictive regressions, $\Delta i_{t+h} = i_{t+h} - i_t = a_0 + a_1 cc_t + a_2 \Delta cc_t + v_{t+h}$, where $\Delta i_{t+h} = i_{t+h} - i_t$ is h-period ahead log growth in investment, cc_t is cyclical consumption, and $\Delta cc_t = cc_t - cc_{t-1}$ is the change in cyclical consumption. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc	0.469	0.958	1.608	1.476	0.474	0.509	0.021
t-stat	2.730	3.148	3.138	1.986	0.660	0.848	0.033
$\overline{R}^2$	0.050	0.067	0.063	0.020	-0.002	-0.003	-0.004
Δcc	0.493	1.019	1.780	1.885	1.051	1.363	1.249
t-stat	2.841	3.279	3.281	2.156	1.124	1.746	1.761
cc	-0.053	-0.136	-0.385	-0.910	-1.279	-1.584	-1.975
t-stat	-1.703	-2.068	-2.944	-3.209	-2.898	-2.888	-3.481
$\overline{R}^2$	0.056	0.085	0.117	0.154	0.194	0.252	0.331

Table 6. Employment Predictability: Change in the Discount Rate

The table presents results of predictive regressions, $\Delta e_{t+h} = e_{t+h} - e_t = a_0 + a_1 cc_t + a_2 \Delta cc_t + u_{t+h}$, where $\Delta e_{t+h} = e_{t+h} - e_t$ is h-period ahead log growth in employment, cc_t is cyclical consumption, and $\Delta cc_t = cc_t - cc_{t-1}$ is the change in cyclical consumption. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc	0.200	0.351	0.554	0.639	0.480	0.456	0.258
t-stat	4.461	4.154	3.745	2.688	1.586	1.354	0.702
$\overline{R}^2$	0.123	0.109	0.084	0.040	0.012	0.006	-0.002
Δcc	0.203	0.364	0.595	0.750	0.652	0.737	0.680
t-stat	4.545	4.190	3.791	2.776	1.812	1.836	1.490
cc	-0.008	-0.028	-0.091	-0.246	-0.381	-0.522	-0.678
t-stat	-0.988	-1.503	-2.231	-2.606	-2.451	-2.444	-2.553
$\overline{R}^2$	0.123	0.117	0.116	0.136	0.162	0.213	0.264

Table 7. Investment Predictability: Large and Small Changes in the Discount Rate

The table presents results of predictive regressions, $\Delta i_{t+h} = i_{t+h} - i_t = a_0 + a_1 cc_t + a_2 \Delta cc_{L,t} + a_2 \Delta cc_{S,t} + v_{t+h}$, where $\Delta i_{t+h} = i_{t+h} - i_t$ is h-period ahead log growth in investment, cc_t is cyclical consumption, $\Delta cc_{L,t} = cc_t - cc_{t-1}$ is the change in cyclical consumption that is greater than one standard deviation from the mean, and $\Delta cc_{S,t} = cc_t - cc_{t-1}$ is the change in cyclical consumption that is less than than one standard deviation from the mean. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc large	0.541	1.104	1.750	1.195	0.130	0.041	-0.513
t-stat	2.754	3.173	3.075	1.557	0.171	0.067	-0.949
Δcc small	0.084	0.170	0.847	3.028	2.393	3.030	3.042
t-stat	0.319	0.381	0.996	1.722	1.232	1.303	1.298
$\overline{R}^2$	0.053	0.072	0.062	0.021	-0.001	0.001	0.001
Δcc large	0.575	1.190	1.983	1.728	0.888	1.119	0.842
t-stat	2.877	3.312	3.265	1.902	0.902	1.346	1.344
Δcc small	0.068	0.125	0.723	2.731	1.935	2.635	3.513
t-stat	0.263	0.295	0.936	1.673	1.106	1.283	1.771
cc	-0.057	-0.144	-0.395	-0.902	-1.271	-1.572	-1.964
t-stat	-1.848	-2.209	-3.036	-3.216	-2.898	-2.870	-3.485
$\overline{R}^2$	0.061	0.093	0.119	0.152	0.192	0.250	0.333

Table 8. Employment Predictability: Large and Small Changes in the Discount Rate

The table presents results of predictive regressions, $\Delta e_{t+h} = e_{t+h} - e_t = a_0 + a_1 cc_t + a_2 \Delta cc_{L,t} + a_2 \Delta cc_{S,t} + u_{t+h}$, where $\Delta e_{t+h} = e_{t+h} - e_t$ is h-period ahead log growth in investment, cc_t is cyclical consumption, $\Delta cc_{L,t} = cc_t - cc_{t-1}$ is the change in cyclical consumption that is greater than one standard deviation from the mean, and $\Delta cc_{S,t} = cc_t - cc_{t-1}$ is the change in cyclical consumption that is less than than one standard deviation from the mean. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc large	0.208	0.377	0.567	0.537	0.341	0.232	0.033
t-stat	4.088	3.927	3.454	2.302	1.175	0.711	0.095
Δcc small	0.154	0.214	0.485	1.203	1.256	1.662	1.530
t-stat	2.213	1.765	1.887	2.113	1.746	1.843	1.564
$\overline{R}^2$	0.121	0.109	0.080	0.043	0.015	0.015	0.005
Δcc large	0.214	0.394	0.622	0.680	0.566	0.585	0.498
t-stat	4.169	3.981	3.574	2.542	1.620	1.508	1.171
Δcc small	0.151	0.204	0.456	1.123	1.121	1.533	1.691
t-stat	2.199	1.750	1.900	2.170	1.792	1.953	1.915
cc	-0.008	-0.030	-0.093	-0.243	-0.377	-0.515	-0.674
t-stat	-1.051	-1.583	-2.276	-2.614	-2.456	-2.438	-2.557
$\overline{R}^2$	0.121	0.118	0.114	0.136	0.161	0.216	0.268

Table 9. Investment Predictability: Positive and Negative Changes in the Discount Rate

Panel A presents results from predictive regressions of the h-period ahead log growth in investment, $\Delta i_{t+h} = i_{t+h} - i_t$, using the change in cyclical consumption, $\Delta cc_t = cc_t - cc_{t-1}$, as regressor. We split the change in cyclical consumption into positive and negative parts and report results from each specification. Panel B includes the level of cyclical consumption, cc_t, as additional regressor. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Positive and Negative Discount Rate Changes							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc negative	1.010	1.904	3.264	3.530	2.250	2.074	1.353
t-stat	3.162	3.520	3.820	2.880	1.833	1.772	1.073
$\overline{R}^2$	0.084	0.095	0.094	0.044	0.010	0.006	-0.000
Δcc positive	0.308	0.780	1.243	0.612	-0.919	-0.754	-1.399
t-stat	1.447	2.119	1.876	0.571	-0.839	-0.651	-1.047
$\overline{R}^2$	0.004	0.013	0.010	-0.003	-0.002	-0.003	-0.000
Panel B: Controlling for the Level of the Discount Rate							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc negative	1.044	1.992	3.510	4.118	3.078	3.204	3.030
t-stat	3.230	3.609	3.911	2.897	2.060	2.552	2.389
cc	-0.051	-0.134	-0.381	-0.918	-1.293	-1.573	-1.960
t-stat	-1.671	-2.067	-2.976	-3.340	-2.985	-2.914	-3.472
$\overline{R}^2$	0.090	0.113	0.148	0.183	0.213	0.260	0.335
Δcc positive	0.333	0.852	1.456	1.150	-0.148	0.454	0.279
t-stat	1.555	2.276	2.110	0.964	-0.114	0.341	0.230
cc	-0.040	-0.116	-0.350	-0.874	-1.246	-1.528	-1.902
t-stat	-1.256	-1.697	-2.632	-3.180	-2.936	-2.851	-3.395
$\overline{R}^2$	0.006	0.025	0.055	0.122	0.186	0.236	0.315

Table 10. Employment Predictability: Positive and Negative Changes in the Discount Rate

Panel A presents results from predictive regressions of the h-period ahead log growth in employment, $\Delta e_{t+h} = e_{t+h} - e_t$, using the change in cyclical consumption $\Delta cc_t = cc_t - cc_{t-1}$ as regressor. We split the change in cyclical consumption into positive and negative parts and report results from each specification. Panel B includes the level of cyclical consumption, cc_t, as additional regressor. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Positive and Negative Discount Rate Changes							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc negative	0.365	0.637	1.032	1.152	0.882	0.724	0.374
t-stat	4.105	4.150	3.991	2.775	1.704	1.187	0.521
$\overline{R}^2$	0.145	0.127	0.104	0.047	0.015	0.005	-0.002
Δcc positive	0.195	0.346	0.521	0.636	0.460	0.544	0.344
t-stat	3.730	3.195	2.510	1.900	1.109	1.078	0.624
$\overline{R}^2$	0.039	0.036	0.024	0.012	0.001	0.001	-0.003
Panel B: Controlling for the Level of the Discount Rate							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc negative	0.369	0.654	1.089	1.309	1.125	1.089	0.941
t-stat	4.142	4.154	4.012	2.823	1.908	1.627	1.179
cc	-0.006	-0.025	-0.089	-0.245	-0.380	-0.508	-0.663
t-stat	-0.760	-1.331	-2.163	-2.604	-2.463	-2.401	-2.514
$\overline{R}^2$	0.144	0.133	0.135	0.143	0.165	0.204	0.255
Δcc positive	0.197	0.359	0.571	0.782	0.691	0.944	0.929
t-stat	3.805	3.268	2.642	2.170	1.466	1.658	1.514
cc	-0.004	-0.021	-0.081	-0.237	-0.373	-0.506	-0.662
t-stat	-0.402	-1.050	-1.962	-2.558	-2.461	-2.411	-2.532
$\overline{R}^2$	0.036	0.038	0.049	0.102	0.146	0.198	0.254

Table 11. Investment Predictability: Discount Rates and Cash Flow News

The table presents results from predictive regressions of the h-period ahead log growth in investment, $\Delta i_{t+h} = i_{t+h} - i_t$, using discount rates news N_{DR} and cash flow news N_{CF} derived from a VAR. For each regression, the table reports the slope estimates, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
N_{DR}	-0.101	-0.243	-0.431	-0.359	-0.028	0.015	0.170
t-stat	-1.907	-2.673	-2.757	-1.643	-0.141	0.082	0.705
N_{CF}	0.022	0.082	0.184	0.226	0.173	0.035	0.056
t-stat	0.935	2.227	2.783	2.452	2.115	0.447	0.634
$\overline{R}^2$	0.025	0.068	0.087	0.033	0.001	-0.008	-0.007

Table 12. Employment Predictability: Discount Rates and Cash Flow News

The table presents results from predictive regressions of the h-period ahead log growth in employment, $\Delta e_{t+h} = e_{t+h} - e_t$, using discount rates news N_{DR} and cash flow news N_{CF} derived from a VAR. For each regression, the table reports the slope estimates, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
N_{DR}	-0.053	-0.098	-0.161	-0.179	-0.118	-0.098	-0.036
t-stat	-3.926	-3.939	-3.628	-2.615	-1.406	-1.027	-0.331
N_{CF}	0.002	0.018	0.040	0.033	0.013	-0.024	-0.026
t-stat	0.344	1.394	1.831	1.084	0.405	-0.670	-0.675
$\overline{R}^2$	0.085	0.103	0.096	0.036	0.003	-0.003	-0.007

Table 13. 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 the the level and change in 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 sample covers the period from 1954Q1 to 2017Q4.

Panel A: Investment Predictability							
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Δcc	0.101	0.356	0.812	1.156	0.585	1.169	1.127
t-stat	0.940	1.882	2.111	1.621	0.810	2.018	1.860
cc	-0.045	-0.128	-0.384	-0.908	-1.267	-1.634	-2.148
t-stat	-2.204	-2.840	-3.469	-3.131	-2.685	-2.657	-3.306
di	0.385	0.595	0.472	-0.162	-0.530	-0.672	-0.815
t-stat	6.366	4.638	1.916	-0.446	-1.423	-1.947	-2.173
$dgdp$	0.492	0.912	2.037	2.206	1.832	1.223	1.374
t-stat	2.868	2.594	3.256	2.486	1.632	0.923	0.971
$dprofit$	0.061	0.106	0.155	0.234	0.333	0.266	0.175
t-stat	3.336	3.010	2.439	2.254	3.151	2.108	1.356
q	0.009	0.018	0.030	0.035	0.036	0.058	0.096
t-stat	2.366	1.983	1.343	0.685	0.522	0.736	1.184
$\overline{R}^2$	0.407	0.397	0.321	0.217	0.240	0.277	0.363

Panel B: Employment Predictability							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Δcc	0.077	0.143	0.280	0.446	0.375	0.457	0.357
t-stat	2.617	2.535	2.303	2.101	1.455	1.761	1.159
cc	-0.010	-0.031	-0.091	-0.230	-0.348	-0.480	-0.626
t-stat	-2.336	-2.644	-2.874	-2.762	-2.477	-2.423	-2.469
di	0.675	1.048	1.234	1.017	0.830	0.937	0.885
t-stat	8.114	5.516	2.936	1.441	1.099	1.063	0.785
$dgdp$	-0.010	0.066	0.283	0.442	0.503	0.404	0.553
t-stat	-0.194	0.672	1.806	1.879	1.857	1.129	1.391
$dprofit$	0.013	0.024	0.028	0.036	0.049	0.026	-0.002
t-stat	2.408	2.091	1.397	1.101	1.343	0.679	-0.064
q	0.001	0.001	-0.000	-0.008	-0.016	-0.022	-0.023
t-stat	0.630	0.437	-0.077	-0.625	-0.846	-0.924	-0.907
$\overline{R}^2$	0.567	0.485	0.328	0.215	0.213	0.245	0.288

Table 14. Alternative Discount Rate Proxies.

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 other discount rate proxies. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Multivariate Investment Growth Predictability							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	-0.025	-0.075	-0.217	-0.549	-0.883	-1.204	-1.782
t-stat	-0.851	-1.245	-1.812	-2.075	-1.918	-2.045	-3.038
dp	0.004	0.006	0.017	0.043	0.056	0.056	0.038
t-stat	0.930	0.677	0.825	1.061	1.079	0.982	0.666
tms	0.461	0.924	1.870	2.883	2.834	2.668	1.783
t-stat	3.439	3.181	3.331	2.729	1.962	1.877	1.702
def	-2.028	-3.405	-5.250	-6.321	-5.931	-6.599	-7.841
t-stat	-4.553	-3.767	-3.465	-2.834	-1.906	-1.613	-1.939
$rrel$	0.643	1.148	1.642	0.712	-0.005	-0.084	-0.230
t-stat	3.287	3.270	2.798	0.634	-0.004	-0.086	-0.243
cay	-0.088	-0.174	-0.339	-0.368	-0.383	-0.601	-0.913
t-stat	-1.351	-1.151	-0.970	-0.520	-0.414	-0.613	-0.994
$\overline{R}^2$	0.282	0.273	0.234	0.227	0.264	0.300	0.368

Panel B: Multivariate Employment Growth Predictability							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
cc	0.013	0.016	0.005	-0.062	-0.164	-0.303	-0.480
t-stat	1.491	0.834	0.140	-1.026	-1.770	-2.307	-3.153
dp	0.004	0.008	0.018	0.037	0.048	0.054	0.058
t-stat	3.840	3.205	3.238	3.309	3.094	2.665	2.486
tms	0.153	0.310	0.616	0.988	1.007	0.754	0.405
t-stat	4.230	3.735	3.831	3.288	2.465	1.844	1.072
def	-0.608	-1.152	-1.982	-2.959	-3.088	-3.032	-3.259
t-stat	-5.264	-4.646	-4.185	-3.425	-2.376	-1.819	-1.871
$rrel$	0.156	0.229	0.260	-0.069	-0.312	-0.470	-0.586
t-stat	3.268	2.509	1.546	-0.211	-0.845	-1.191	-1.320
cay	-0.036	-0.080	-0.157	-0.278	-0.403	-0.516	-0.717
t-stat	-1.963	-1.903	-1.737	-1.689	-1.755	-1.927	-2.336
$\overline{R}^2$	0.255	0.235	0.228	0.289	0.329	0.354	0.433

Table 15. Alternative Detrending

Panel A, B, and C present results from predictive regressions of h-period ahead log stock returns, investment growth, and employment growth. As predictive variable, we use cyclical consumption defined either as the residual in a quadratic trend specification, $c_t = \beta_1 + \beta_2 t + \beta_3 t^2 + \omega_t$, or defined by assuming that consumption follows a random walk such that the Hamilton filter implies that $cc_t = c_t - c_{t-k}$ where $k = 6$ years. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Stock Return Predictability							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Quadratic trend							
cc	-0.606	-1.197	-2.355	-4.345	-5.470	-6.697	-7.377
t-stat	-3.708	-3.731	-3.603	-4.337	-5.927	-7.351	-5.845
$\overline{R}^2$	0.039	0.073	0.148	0.283	0.345	0.411	0.387
Random walk							
cc	-0.360	-0.714	-1.382	-2.463	-3.227	-4.379	-5.380
t-stat	-3.234	-3.850	-4.229	-4.372	-4.769	-5.766	-6.682
$\overline{R}^2$	0.033	0.062	0.124	0.221	0.293	0.423	0.466
Panel B: Investment Growth Predictability							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Quadratic trend							
cc	-0.028	-0.133	-0.552	-1.703	-2.645	-3.207	-3.475
t-stat	-0.538	-1.159	-2.208	-3.560	-4.597	-5.315	-5.010
$\overline{R}^2$	-0.002	0.005	0.049	0.209	0.372	0.467	0.488
Random walk							
cc	-0.026	-0.083	-0.284	-0.757	-1.108	-1.349	-1.709
t-stat	-0.838	-1.348	-2.456	-3.187	-3.017	-2.543	-2.844
$\overline{R}^2$	-0.001	0.005	0.030	0.091	0.158	0.197	0.264
Panel C: Employment Growth Predictability							
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
Quadratic trend							
cc	0.004	-0.019	-0.124	-0.460	-0.780	-1.028	-1.196
t-stat	0.250	-0.602	-1.695	-3.086	-3.693	-3.679	-3.237
$\overline{R}^2$	-0.004	-0.002	0.025	0.150	0.279	0.361	0.389
Random walk							
cc	0.005	-0.003	-0.046	-0.168	-0.277	-0.377	-0.501
t-stat	0.608	-0.156	-1.206	-1.983	-1.983	-1.918	-1.955
$\overline{R}^2$	-0.003	-0.004	0.006	0.046	0.083	0.114	0.151

Figure 1. Cyclical Consumption