Production, Consumption, and Time Varying Expected Returns

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Abstract

This paper develops an empirical test of the q-theory production based asset pricing model using a general equilibrium result in the presence of habit utility and adjustment costs of investment. It must be the case that when the consumption surplus predicts stock returns corresponding investment patterns predict investment returns in exactly the same way. The no arbitrage condition also implies investment patterns must also predict stock returns in the same way as the consumption surplus. Using this insight we find strong empirical support for the production based model without the difficulties of calculating investment returns. Consequently, previous rejections of the model most likely stem from the failure of one or more of the many assumptions that are needed to construct investment returns.

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1 Introduction

This paper describes and performs an empirical test of the q-theory production based asset pricing model that avoids difficulties in measuring investment returns. We do this by appealing to a general equilibrium result that with habit in consumption and adjustment costs in investment it must be the case that just as the consumption surplus predicts future time varying expected stock returns, corresponding investment patterns for firms from the production side predicts time varying expected investment returns in exactly the same way. This result follows from the no arbitrage condition linking the consumer to the manager of the firm. We use this relationship to form a new test of the investment model. In particular, in a general equilibrium framework the following predictive regressions are all equivalent in that they should lead to identical results:

$$\begin{aligned} r_t^S &= a^S + b^S * cs_{t-1} + u_t \\ r_t^I &= a^I + b^I * ip_{t-1} + v_t \end{aligned}$$

where r^S is the stock return, cs is consumption surplus, r^I is the investment return, ip is the investment gap, and u and v are error terms. In the general equilibrium setting because of no arbitrage, the following are also equivalent and lead to identical results:

$$\begin{aligned} r_t^S &= \alpha^S + \beta^S * ip_{t-1} + u_t \\ r_t^I &= \alpha^I + \beta^I * cs_{t-1} + v_t \end{aligned}$$

It is necessary that $b^S * cs_{t-1} = b^I * ip_{t-1} = \beta^S * ip_{t-1} = \beta^I * cs_{t-1}$ for the production model to hold and hence the general equilibrium framework to be confirmed. The contribution of this paper is to show how to test the production based model by appealing to this general equilibrium results. In particular, it is not necessary to estimate all four regressions above to test the model. Instead, it is possible to avoid the construction of investment returns and in stead simply estimate:

$$\begin{aligned} r_t^S &= a^S + b^S * cs_{t-1} + u_t \\ r_t^S &= \alpha^I + \beta^S * ip_{t-1} + v_t \end{aligned}$$

and if $b^S * cs_{t-1} = \beta^S * ip_{t-1}$ then this provides support for the production based model since it implies that investment returns must be equal to stock returns. Furthermore, given we match both the consumption and the investment side, finding that $b^S * cs_{t-1} = \beta^S * ip_{t-1}$ would provide support for a general equilibrium interpretation of the consumption and investment decision. All we need to estimate the above two predictive regressions is to construct the consumption surplus, cs and the investment gap, ig.

The reason why we can focus on cs and ig is that there exists a very close mapping between the investment decisions that a manager makes and the consumptions decisions that an investor makes. This connection is the the central tenant of the production based model and is based on the manager adjusting investment such that the marginal rate of transformation is equal to the investor's marginal rate of substitution. This process eliminates any arbitrage profits between stock market valuations and the value of the firm's investments. In a general equilibrium setting a natural result of this behavior is that investment returns will be equal to stock returns, which is the central prediction of the production based model, but is achieved without the need to calculate investment returns.

The approach that we take to test the production based model is to draw on Cochrane (1991), Zhang (2017), and Cochrane (2020) who show that the production based model[1], and the consumption CAPM (CCAPM) are equivalent. In the CCAPM stock market returns are derived from a utility function that uses the marginal rate of substitution of an investor that is inferred from consumption data. In the production based model, investment returns

[1] The production based model is sometimes refered to as the investment CAPM when undertaking cross-sectional analysis. As we focus on time-series predictability tests we refrain from the using the term the investment CAPM.

are derived from a production function using the marginal rate of transformation that is inferred from investment data. The manager of the firm makes investment decisions that ensure the investment return is equal to the stock market return which then brings about the equivalence of the production model and the CCAPM.

Using the logic outlined above, we can form a test of the production model by following the general equilibrium implications of the models with habits in consumption and adjustment costs of investment. We track movements in the aggregate stock market expected return through the representative investor's consumption decisions as measured through a utility function that displays habit formation, as in Campbell and Cochrane (1999). As consumption rises above the habit level giving high surplus consumption, the marginal utility from further consumption today falls and investment into the stock market increases to fund an increase in more valuable future consumption. This causes future expected returns to fall. The manager of the firm must now invest more in physical assets, pushing up investment today which leads to future investment having a lower marginal rate of transformation and hence lower future investment returns. Failure to do this would drive a wedge between investment returns and stock returns leading to arbitrage profits that can be exploited by the manager of the firm selling the stock at a high price and investing the proceeds in the firm at a low price. They will continue to do this until investment returns are equal to stock returns.

From this process of ruling out arbitrage profits which equates investment returns and stock returns, it is clear that variations in the expected aggregate stock market return that are driven by the consumption surplus ratio, which we refer to as consumption fluctuations around the habit level, should be matched closely by variations in investment returns driven by investment fluctuations around a similar trend as the consumption habit. Consequently, there should be a very close mapping between consumption fluctuations, which capture how consumption moves relative to habit and represent the time-varying stock market return, and investment fluctuations which should measure time varying investment returns. The equality of these two illustrate that the investment decisions of managers mirror the consumption decisions of investors in order to ensure that investment returns are equal to stock returns.

We can test the implications of the production based model in three ways. First, from the habit model, the consumption surplus ratio informs us of the marginal utility of current and future consumption and hence future expected stock market returns. Atanasov, Møller, and Priestley (2020) provide simulations which show that consumption detrended around a long run trend approximates the surplus consumption ratio in the Campbell and Cochrane (1999) habit model. In a general equilibrium setting, if a manager of a firm acts in a way to equalize investment returns and stock returns, then it must follow that investment will also move around a trend in the same way that consumption does. Therefore, the first condition we require is that there exists a close time series relation between investment and consumption movements around the same specification of the trend that reflects consumption habits. This means that they should be highly correlated in the data.

Second, in the Campbell and Cochrane (1999) habit model the surplus consumption ratio predicts variation in future expected stock returns. Given the no arbitrage mechanism that we outline above, it must also be the case that investment which is detrended around a long run trend can predict stock returns in a similar fashion if stock returns are equal to investment returns. Whereas detrended consumption predicts stock returns because the surplus consumption ratio signals the investor's view of future stock returns, detrended investment predicts investment returns because it signals the manager's view of future investment returns. However, as outlined above, rather than having to calculate investment returns, we can instead examine if investment fluctuations predict stock returns in the same way as consumption fluctuations predict stock returns. The reason for this is that in a general equilibrium setting if the production model holds stock returns are equal to investment returns and a regression of stock returns on investment fluctuations is the same as a regression of stock returns on consumption fluctuations.

Third, we can exploit the observation from the extant literature that proxies for the aggregate risk premium are also able to forecast macroeconomic quantities. For example, both employment growth and investment growth can be affected by variation in the equity market risk premium. Lettau and Ludvigson (2002) derive the result that variations in the equity market risk premium should predict long run investment growth. Chen and Zhang (2011) provide a model and evidence regarding the predictability of employment growth by the equity market risk premium. Møller and Priestley (2020) provide empirical evidence that consumption fluctuations predict both investment and employment growth. It should be the case that if consumption fluctuations can predict these macroeconomic quantities, then investment fluctuations should also predict them. Therefore, if the production model holds, investment fluctuations should also predict employment and investment growth and predict them to the same extent as consumption fluctuations.

We find strong support for the production based production model and hence a general equilibrium model with habits in consumption and adjustment costs of investment. First, consider Figure 1 which plots consumption fluctuations and investment fluctuations around a trend. It is clear that they both follow a very similar pattern which is also evident from the correlation coefficient which is 0.64. This provides the first evidence that the manager of the firm does adjust investment in line with the consumption pattern of the investor. Second, we show that a regression of aggregate stock returns on investment fluctuations provides evidence of stock return predictability that is very similar to that of when using consumption fluctuations. For example, at the one quarter horizon, the estimated coefficient from regressing excess stock returns on the one quarter lagged standardized investment fluctuations is -0.014 (t=2.74) with an adjusted R^2 ($\overline{R}^2$) of 2.7%. The corresponding estimated coefficient when regressing excess stock returns on standardized consumption fluctuations is -0.015 (t=3.18) with an $\overline{R}^2$ of 3.4%. We are unable to reject the null hypothesis that these two estimated coefficients are equal.[2] We find consistent results across horizons, across different ways to detrend investment and consumption, in different sub-samples, for different measures of consumption, and we find that consumption and investment fluctuations predict

[2]Note that in the empirical tests we standardize consumption and investment fluctuations such that the condition $b^S * cs_{t-1} = \beta^S * ip_{t-1}$ is reduced to simply $b^S = \beta^S$.

stock return similarly in bad states, as defined as NBER recessions, and similarly in good states. There is no evidence of any difference in the ability of consumption fluctuations and investment fluctuations to predict returns.

The third findings we present are based on predicting macroeconomic quantities. We run regressions where we predict investment growth and employment growth with both consumption fluctuations and investment fluctuations. We find consistent results across regressions that show both investment fluctuations and consumption fluctuations can forecast macroeconomic quantities to a very similar extent. This indicates that both consumption and investment fluctuations are close substitutes as proxies for the time varying risk premium, further supporting the production based model.

The results we present are important for two reasons. First, they provide support for a general equilibrium framework with consumption habits and investment adjustment costs. Second, recent research has raised questions about the usefulness of the economic mechanisms that underpin the production based model. Cochrane (1991) presents some supportive evidence in that the estimated coefficients on variables that stock returns and investment returns are regressed on are similar, although often noisy. However, the dividend price ratio predicts the two differently. Cochrane (1991) also regresses stock returns and investment returns on the investment to capital ratio. While both regressions return negative estimates at short horizons, turning positive at longer horizons, the stock return estimates are shifted forward in time. Furthermore, the stock return multiple regressions coefficients have a pattern that is different to those of the investment returns multiple regression coefficients. In addition, the correlation of investment returns and stock returns, which should be one, is low at the quarterly horizon at 0.24, but rises at the annual horizon to 0.45.

Liu, Whited and Zhang (2009) find mixed results when estimating the structural parameters that are needed to equate stock return with investment returns at the portfolio level. For example, the model can explain value and post announcement drift anomalies separately, but not jointly. In addition, when imposing that the mean and variance of stock returns are the same as those for investment returns, the pricing errors are large. Liu and Zhang (2014) show that the production based model can not explain momentum and value anomalies simultaneously. They show that the estimated capital share parameter and the estimated adjustment cost parameter vary across portfolio sorts. Campbell (2018) notes that the need to have different estimates of these two parameters across different characteristic sorted portfolios is a common theme in asset pricing q theories and therefore a serious critique in testing production based asset pricing models. It should be noted that Gonçalves, Xue, and Zhang (2019) show that including working capital in the production function and addressing issues regarding aggregation does help improve the performance of the production model.

In perhaps the most serious critique of the production model, Delikouras and Dittmar (2018) find strong rejections of the test that investment returns are equal to stock returns when jointly estimating the model and imposing the existence of a minimum variance stochastic discount factor that simultaneously satisfies Euler equations for both investment and stock returns. They also perform tests that lead to a questioning of the usefulness of the cross-sectional q-factor model of Hou, Xue, and Zhang (2015) and the Fama and French (2015) five factor model, both of which include factors inspired by the production based investment model, namely an investment and a profitability factor. Delikouras and Dittmar (2018) conclude that the claim in Liu and Zhang (2013) that the production model is the new paradigm for cross-sectional asset pricing is premature.

Given the recent focus on the production based model and the prevalence of new factor models that emanate from the production model, it is important to understand why recent papers have rejected the production model. It is not necessarily the case that a rejection of some of the predictions of the model signifies a failure of the economic mechanisms that underlie the model and hence the usefulness of factors that are derived from the model. In fact, testing the model when using investment returns is a test of a joint hypothesis of, on the one hand, the underlying predictions of the theory and, on the other hand, that all of the many assumptions that go into calculating investment returns also hold. Examples of the assumptions that are required to calculate investment returns are: the form of the production function, the form of the adjustment costs, the requirement that the capital share and adjustment costs parameters are the same across test assets, the timing alignment of investment and stock returns, the measurement of data in the production function, inclusion or exclusion of leverage and taxes, the choice of depreciation rates, and the specification of the production function in terms of omitting labor, intangibles, and working capital, amongst others. If any of these assumptions are incorrect it could lead to a rejection of the test that investment returns are equal to stock returns and not necessarily a rejection of the economic mechanisms of the production model.

Due to the fact that there are so many different specifications of the production function and many different assumptions that need to be made in order to calculate investment returns, we believe it is an important contribution to consider an alternative way to test the production model that avoids the troublesome construction of investment returns. If we do find support for the production model through tests that do not require the construction of investment returns, then we become informed that previous rejections of the model stem from a rejection of one or more of the assumptions that underlie the construction of the investment returns rather than a rejection of the production model. Support for the production model through our tests will also inform us that factors derived by, for example, Hou, Xue, and Zhang (2015) and Hou, Mo, Xue, and Zhang (2020) that are based on investment and profitability and are used in cross-sectional asset pricing models, can be interpreted as factors than emanate from the economic mechanisms that underlie the production model. This is important since these factor models are becoming the workhorses of empirical asset pricing. Furthermore, if we find support for the production model it means that refining models to calculate investment returns is a fruitful avenue for future research.

The paper proceeds as follows. In section 2, we discuss the production model and show how we can test implications of the theory without having to construct investment returns.

Section 3 presents the data on investment and consumption fluctuations. We provide tests of the production model in section 4 that focus on predictive regressions using investment and consumption fluctuations. Section 5 concludes.

2 The Q-Theory Production Based Model

In this section of the paper, we review the production based model and illustrate where our tests of this model arise from. This section draws heavily on Cochrane (1991) and Zhang (2017). The production based model is derived from the first order conditions of the producer (manager) and it is analogous to the CCAPM which is derived from the first order conditions of the consumer (investor). The production model uses a production function and derives *investment* returns from the marginal rate of transformation. The CCAPM uses a utility function and derives *stock* returns from the marginal rate of substitution. In general equilibrium stock returns are equal to investment returns because the marginal rate of transformation must be equal to the marginal rate of substitution. The absence of this condition leads to arbitrage profits that would be exploited by the manager of the firm.

Cochrane (1991) shows that the manager of a firm has a first order condition that relates the investment return to the stock return. This requires the assumption of complete markets where the manager is free to trade a portfolio of assets in a way that matches the state by state payoff of the investment returns. The no arbitrage condition can be enforced by the manager of the firm trading this portfolio of assets in the stock market and altering their investment in physical assets at the firm level. For example, if the manager can buy the mimicking portfolio of assets for a price greater than one, then the manager shorts this portfolio, invests the proceeds in physical assets, pays off the mimicking portfolio with the investment return proceeds and pockets a sure profit. This process of investment adjustment continues until the point where the investment return equals the mimicking portfolio return that is traded in the market, that is, until investment returns are equal to stock returns.

This is simply the point where the firm's marginal rate of transformation is equal to the consumers marginal rate of substitution.

It follows that the most simple test of the production based model is to test the null hypothesis that investment returns are equal to stock returns. This requires the construction of investment returns. Following Cochrane (1991) and adopting the notation of Lui, Whited, and Zhang (2009), Zhang (2017), and Gonçalves, Xue, and Zhang (2019), we show first, how to derive investment returns and then second, that investment returns are equal to stock returns.

Assume that firm i invests in physical capital at time t, defined as I_{it}, in order to produce an homogeneous product. Let K_{it} denote the stock of physical capital and X_{it} denote a vector of aggregate and firm specific shocks. We can then define the profit function as:

$$\Pi_{it} \equiv \Pi\left(K_{it}, X_{it}\right)$$

The profit function is assumed to have constant returns to scale and the production function is Cobb-Douglas. The marginal product of capital is parameterized according to Gilchrist and Himmelberg (1998) as the output to capital ratio: $\gamma_K \frac{Y_{it}}{K_{it}}$ with γ_K representing the share of physical capital in output Y_{it},. Capital evolves according to:

$$K_{it+1} = I_{it} + \left(1 - \delta_{it}\right) K_{it}$$

where δ_{it} is the depreciation rate. There are adjustment costs associated with new investment, $\Phi_{it}(I_{it}, K_{it})$ where the function is quadratic:

$$\Phi_{it} = \frac{a}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it}$$

and $a > 0$ is the adjustment cost parameter. Investment returns, r^K_{it+1} are given as:

$$r^K_{it+1} = \frac{\left[\gamma_K \frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right] + (1-\delta_{it+1})\left[1 + a\left(\frac{I_{it+1}}{K_{it+1}}\right)\right]}{1 + a\left(\frac{I_{it}}{K_{it}}\right)} \tag{1}$$

The numerator depicts the marginal benefit to investment at time $t+1$ comprising of the marginal product of capital $\gamma_K \frac{Y_{it+1}}{K_{it+1}}$, the marginal reduction in investment adjustment costs $\frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2$, and the marginal continuation value of a net of depreciation extra unit of capital $(1-\delta_{it+1})\left[1 + a\left(\frac{I_{it+1}}{K_{it+1}}\right)\right]$ which is the marginal cost of investment in time $t+1$. The denominator states the marginal cost of investment at time t.

Given a stochastic discount factor from the stock market, M_{t+1}, the manager chooses I_{it} in order to maximize the cum-dividend market value of equity at time t:

$$P_{it} + D_{it} = \max_{\{I_{it}\}} \left[X_{it}K_{it} - I_{it} - \frac{a}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it}\right] + E_t\left[M_{t+1}X_{it+1}K_{it+1}\right] \tag{2}$$

The first principle of investment states

$$1 + a\left(\frac{I_{it}}{K_{it}}\right) = E_t\left[M_{t+1}X_{it+1}\right] \tag{3}$$

where the left hand side is the marginal cost of investment, set equal to 1 plus the marginal adjustment costs, and the right hand side is marginal q which measures the marginal benefits of investment at time t as measured by the marginal product of capital in terms of its present value.

Cochrane (1991) derives the above first principle without $M_{t+1.}$ Note that $D_{it} = X_{it}K_{it} - I_{it} - \frac{a}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it}$ and therefore the ex-dividend equity value of the firm at the optimum is

$$P_{it} = E_t\left[M_{t+1}X_{it+1}K_{it+1}\right] \tag{4}$$

The stock return is:

$$r^S_{it+1} = \frac{P_{it+1} + D_{it+1}}{P_{it}} = \frac{X_{it+1}K_{it+1}}{E_t\left[M_{t+1}X_{it+1}K_{it+1}\right]} = \frac{X_{it+1}}{E_t\left[M_{t+1}X_{it+1}\right]} \tag{5}$$

Combining (3) and (5) gives

$$r^S_{it+1} = \frac{X_{it+1}}{1 + a\left(\frac{I_{it}}{K_{it}}\right)} \tag{6}$$

The manager invests until the date t marginal cost of investment is equal to the time $t+1$ marginal benefit of investment discounted with the stock market returns to date t value. Equation (6) is the same as the definition of investment returns in equation (1) with $X_{it+1} = \left[\gamma_K \frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right] + (1 - \delta_{it+1})\left[1 + a\left(\frac{I_{it+1}}{K_{it+1}}\right)\right]$. Therefore from (6) and (1) we see that $r^S_{it+1} = r^K_{it+1}$.

A natural test of the production model is to test that the moments of stock returns and investment returns are the same. Cochrane (1991) notes that at the aggregate level there are a number of problems with testing $r^S_{it+1} = r^K_{it+1}$. For example, investment returns include non-listed firms, they excludes debt and taxes, productivity shocks are not measured, and the adjustment for time aggregation is crude. Instead Cochrane (1991) calculates investment returns and exploits implications of the production model to undertake further tests. In particular, anything that predicts stock returns and anything that is predicted by stock returns, should also predict, and be predicted by investment returns. Cochrane (1991) presents promising but mixed results from various regressions. In addition, the correlation of investment returns and stock returns, which should be one, is low at the quarterly horizon at 0.24, although it rises at the annual horizon to 0.45. Cochrane (1991) speculates that differences in estimated regression coefficients and the low correlation between investment returns and stock returns could be eliminated by modifying the production function with alternative forms of technology, different adjustment costs, gestation lags, variations in marginal product, as well as addressing timing issues.

Liu, Whited, and Zhang (2009) build on the work of Cochrane (1991) and formally test if the mean and variance of stock returns are equal to those of investment returns. To overcome some of the problems raised by Cochrane (1991) in testing whether investment returns are equal to stock returns at the aggregate level, Liu, Whited, and Zhang (2009) use portfolio level data, sorted by characteristics, and use GMM to test the moment condition:

$$r^S_{it+1} - \frac{\left[\gamma_K \frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right] + (1-\delta_{it+1})\left[1 + a\left(\frac{I_{it+1}}{K_{it+1}}\right)\right]}{1 + a\left(\frac{I_{it}}{K_{it}}\right)} = 0 \tag{7}$$

through estimation of the structural parameters γ and a. They add to (7) debt and taxes, which we omit from the above for simplicity. They also test that the variance of investment returns is equal to the variance of stock returns, that is, they impose the additional moment condition that $\sigma^2(r^S_{it+1}) - \sigma^2(r^K_{it+1}) = 0$.

Liu, Whited, and Zhang (2009) form portfolios sorted on investment, earnings surprises, and book to market value given that these characteristics provide a large spread in average returns. When focusing solely on matching the mean of stock returns and investment returns the model performs well recording low pricing errors per se and when compared to the pricing errors produced by other asset pricing models. However, the model struggles when having to confront both the mean and variance moment conditions in that pricing errors of the portfolios formed by earnings surprises and investment vary positively with the characteristic and are comparable in size to pricing errors from other asset pricing models. Perhaps even more critical for the performance of the model is that the estimated capital share parameter, γ, and the estimated adjustment cost parameter, a, vary across portfolio sorts, especially the adjustment cost parameter. Campbell (2018) notes that the need to have different estimates of these two parameters across different characteristic sorted portfolios is a common theme in asset pricing q theories and therefore a serious critique in testing investment based asset pricing models.

Aggregation has also been an issue in tests of the production model. For example, Liu, Whited, and Zhang (2009) aggregate firm level data to the portfolio level and subsequently calculate portfolio level investment returns. Gonçalves, Xue and Zhang (2019) note that this practise makes the unrealistic assumption that all the firms in a given portfolio have the same investment rate. It also omits a lot of firm level variation that could be useful in identifying structural parameters. To confront the aggregation problem Gonçalves, Xue and Zhang (2019) examine firm level data and include working capital into the production function of their benchmark model. These modifications do improve the performance of the production model relative to that of Liu, Whited and Zhang (2009) in terms of lower pricing errors and lower cross-sectional distribution of the capital share and adjustment cost parameters. However, the over-identifying tests reject the model and hence the production model.

In what is the most serious critique of the production model, Delikouras and Dittmar (2019) provide empirical results that not only reject the investment based CAPM, but also questions the usefulness of factor models such as Hou, Xue, and Zhang (2015) that are inspired from the production based investment model. Delikouras and Dittmar (2019) consider one of the testable implications of the production model which Cochrane (1991) shows must hold. Namely that when projecting a stochastic discount factor on both stock returns and investment returns it should produce the same coefficients. This is the same as saying that a stochastic discount factor that is a linear combination of stock returns should satisfy the Euler equation for investment returns. Delikouras and Dittmar (2019) show that this condition is impossible to satisfy in the data in that a stochastic discount factor can not satisfy Euler equations for both stock and investment returns for portfolios formed in investment and the return on equity (profitability). The pricing errors on these portfolios are large and statistically significant. Even after relaxing some of the assumptions such as having different production parameters across portfolios, using annual as opposed to quarterly returns, and considering alternative timing conventions, the model is always rejected.

Overall, Delikouras and Dittmar (2019) conclude that the production based investment model that generates investment returns is not able to match Euler equations and consequently the model will not provide a complete description of the cross sectional variation in stock returns. This in itself questions whether the risk premia on investment and profitability factors that are derived from this model such as those used in Hou, Xue and Zhang (2015) and Hou, Mo, Xue, and Zhang (2020), and also used in Fama and French (2016) are indeed related to a firm's optimal investment decisions. Based on the negative evidence regarding the performance of the production model, Delikouras and Dittmar (2019) argue that Liu and Zhang's (2013) claim that the success of investment based asset pricing models has led these models to be the new paradigm in asset pricing is premature.

Another criticism of investment based models is Golubov and Konstantinidi (2018) who show that the investment based models of Kogan and Papanikolaou (2014) and Zhang (2005) are unable to explain the value effect and cost doubt on the ability of the investment based models to explain cross-sectional anomalies.

The implications of rejections of the different specifications of production based investment model can be set into two categories. Either it is due to a failure of the economic mechanism of the investment based model. In this case, the whole idea that the investment based CAPM offers a new paradigm to understand asset prices needs to be reassessed. Or, these rejections are due to one, or potentially more, of the many assumptions that have to be made when calculating investment returns failing to hold. These assumptions are amongst others: i) misspecification of the production function which means the functional form of the investment return is misspecified. This could be due to, for example, omission from the production function of labour, brand and knowledge capital, and intangibles. For example, Belo, Gala and Vitorino (2018) find that physical capital makes up only fifty percent of firm value and consequently other factors should be included in the production function. ii) rejections of the assumption that the capital share and adjustment cost parameters are the same across test assets. iii) uncertainty regarding the timing of investments and when they are impacted on stock returns, for example, investment plans forecast future stock returns (Lamont (2000)). iv) aggregating from firm to portfolio or the aggregate level assumes that firms in the same portfolio have the same investment rates. v) there are problems in measuring the investment to capital ratio; should investment be measured based on orders, deliveries, payments or some combination of them, and how is capital valued when there is no liquid market for old capital stock? vi) the inclusion of debt an taxes.

It is clear that any rejection of the investment based asset pricing model that necessitates the calculation of investment returns could be due to either a failure of the underlying economic mechanisms or due to one or more of the assumptions that have to be made in order to calculate investment returns being incorrect. In essence, to date tests of the investment based CAPM involves a joint hypothesis of the model and the assumptions require to calculate investment returns. The aim of this paper is to avoid this joint hypothesis problem by developing tests of the production model that avoid the need to calculate investment returns.

2.1 Testing the Q-theory Production Model

We propose an alternative way to test the production model that gets round the joint hypothesis problem by circumventing the need to calculate investment returns. Cochrane (1991) and Zhang (2017) show that the production model and the consumption CAPM (CCAPM) are equivalent. In the CCAPM stock market returns are derived from a utility function that uses the marginal rate of substitution of investors that is inferred from consumption data. In the production model investment returns are derived from a production function using the marginal rate of transformation that is inferred from investment data. In order to avoid arbitrage profits, in complete markets, the manager of the firm makes investment decisions that ensure the investment return of the firm is equal to the stock market return which is determined by investors' marginal rates of substitution, or the stochastic discount factor.

Using the logic outlined above, we can form a test of the production model in the following way. First, we follow Campbell and Cochrane (1999) by specifying the investor's utility function to exhibit external habit formation which is defined indirectly through the surplus consumption ratio $S_t \equiv \frac{C_t - H_t}{C_t}$ where C_t is consumption and H_t is the time-varying subsistence level of consumption. Campbell and Cochrane (1999) assume that the log surplus consumption ratio, $s_t \equiv \log(S_t)$, follows a mean-reverting heteroscedastic first-order autoregressive process:

$$s_{t+1} = (1-\phi)\,\overline{s} + \phi s_t + \lambda(s_t)\,\upsilon_{t+1}, \tag{8}$$

where $\overline{s}$ is the steady state value of s_t, ϕ is the habit persistence parameter, and $\lambda(s_t)$ is a nonlinear monotonically decreasing sensitivity function that determines how innovations in consumption growth υ_{t+1} influence s_{t+1}. Surplus consumption is the state variable in the model and it controls the price of risk and generates time-variation in expected returns. It is this that we are going to extract by estimating cyclical consumption.

Wachter (2006) shows that a first-order approximation around $s_t = \overline{s}$ implies that surplus consumption adjusts gradually to the history of current and past consumption with coefficient ϕ:

$$s_t \approx \kappa + \lambda(\overline{s}) \sum_{j=0}^{\infty} \phi^j \Delta c_{t-j}, \tag{9}$$

where κ is a constant depending on model parameters. Assuming a close to unity value of the persistence parameter ($\phi \approx 1$), it follows that there exists a close link between a finite-horizon proxy of surplus consumption and cyclical consumption developed in Atanasov, Møller and Priestley (2020):

$$\hat{s}_t \approx c_t - c_{t-k} \approx cc_t, \tag{10}$$

where c_t is log real consumption and k determines how long habit reacts to past consumption.

The Campbell and Cochrane (1999) model, under the assumption that excess returns on the stock market and consumption growth are jointly conditionally lognormally distributed, gives:

$$E_t\left(r^s_{t+1}\right) + \frac{1}{2}\sigma_t^2 = \gamma_t cov_t\left(r^s_{t+1}, \Delta c_{t+1}\right), \tag{11}$$

where $E_t\left(r^s_{t+1}\right)$ is the expected log excess stock return, γ_t is the state-dependent price of consumption risk defined as $\gamma_t = \gamma(1 + \lambda(s_t))$, $cov_t\left(r^s_{t+1}, \Delta c_{t+1}\right)$ is the amount of risk, and $\frac{1}{2}\sigma^2_t$ is a Jensen's inequality term. Since $\lambda(s_t)$ is inversely related to s_t, and cc_t and s_t are tightly linked as they both depend on past consumption growth, it follows that low levels of cyclical consumption, where consumption approaches habit, increase γ_t and forecast high expected returns. This turns out to be consistent with both simulations of the Campbell and Cochrane (1999) model and empirical results based on predicting actual stock returns presented in Atanasov, Møller, and Priestley (2020).[3]

We now turn to discussing how the mechanisms that drive the risk premium from the consumption side must be matched by managers of firms in their investment decisions to ensure that no arbitrage profits between stock returns and investment returns arise. As the stock market expected return varies over time given the investor's consumption patterns as measured by s_t, the manager of the firm must adjust the investment level in the firm such that the investment return tracks the time varying stock market return. The result of this is that consumption fluctuations that proxy s_t, which track time variation in expected stock returns from the utility function of a consumer that exhibits habit formation, will fluctuate very similarly to investment fluctuations which track time variation in expected investment returns from the production function of a firm that faces adjustment costs. This is necessary to avoid arbitrage profits. From this, we can test the implications of the production based production model. First, we can examine the time series relation between aggregate investment and aggregate consumption as they move around a trend in order to see how closely they fluctuate together. Second, we can exploit the finding that cyclical consumption which proxies the consumption surplus ratio predicts stock returns at short and long horizons. The implication of this is that cyclical investment must also predict stock returns in the same way and to the same extent if the production model holds. If it does investment returns are equal to stock returns.

[3] Note also that the inverse relation between s_t, and therefore cc_t, and risk premia operates also via the conditional covariance term in Equation (11) because a fall in consumption toward the habit in bad times is associated with a rise in $cov_t\left(r^s_{t+1}, \Delta c_{t+1}\right)$ in the model.

In sum, whereas consumption fluctuations predict stock returns because consumption fluctuations signal the investor's view of future stock returns, investment fluctuations predict investment returns because investment fluctuations signal the manager's view of future investment returns. If investment returns are equal to stock returns then both consumption fluctuations and investment fluctuations predict stock returns in the same way. To assess this, we undertake the following regression:

$$r^S_{t+1} = a_{cc} + b_{cc} * cc_t + u_t$$

$$r^S_{t+1} = a_{ci} + b_{ci} * ci_t + v_t \tag{12}$$

where r^S_{t+1} is the stock market excess return, cc is standardized cyclical consumption, ci is standardized cyclical investment, and u and v are residuals. We should observe that $b_{cc} = b_{ci}$ and can test this with a Wald test.

There are a number of other additional tests that can be performed in order to provide support to this basic test of the production model. First, we examine if $b_{cc} = b_{ci}$ in good times and bad times.[4] This is a concern because good times are by far the most prevalent times in the data. If there is an asymmetry in the extent of predictability of returns using consumption fluctuations, it is interesting to see if this asymmetry is pick up by managers of firms in that investment fluctuations have different predictability in good and bad times. If the production model holds and investment returns are equal to stock returns then we need to see the same estimated coefficients in good times when estimating with consumption fluctuations and investment fluctuations and the same estimated coefficients in bad times when estimating with consumption fluctuations and investment fluctuations.

Second, we also look at different sub samples because Welch and Goyal (2008) highlight that many business cycle predictor variables have performed particularly poorly after the

[4]The extant literature shows that predictor variables are only able to forecast returns in bad times as defined by recessions, but not in good times, that is, during business cycle expansions (Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018)).

oil price crisis in the mid 1970s. However, under the economic mechanisms of both the consumption and production model, we would not expect to observe this. Third, we look at alternative measures of consumption using personal consumption expenditures (PCE) as the measure of consumption that includes all expenditures on all types of consumption; durables, non-durables, and services. Fourth, we examine whether $cc_t - ci_t$ can predict stock returns. The reason for this is that although consumption fluctuations have a reasonably high correlation with investment fluctuations, Figure 1 reveals that there are visible difference in the two series and about a third of the variation in consumption and investment fluctuations is independent of one another. If the production model holds and investment returns are equal to stock returns, then the differences in consumption and investment fluctuations should not be able to forecast stock returns, it is only the common element that should be able to forecast stock returns.

The third way that we can test the production model without having to calculate investment returns is to consider the literature that has shown that variables that can forecast stock returns are also able to forecast macroeconomic quantities. Therefore, if stock returns are equal to investment returns, investment fluctuations should predict macroeconomic variables to the same extent that consumption fluctuations can predict them.

3 Extracting Investment and Consumption Fluctuations

In this section of the paper, we describe how we extract investment and consumption fluctuations. Data on investment is aggregate private nonresidential investment (seasonally adjusted and inflation adjusted). We calculate the growth rate of the natural log of investment. Data on consumption is 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.[5] These two data series are sampled quarterly from the first quarter of 1947 to the fourth quarter of 2017.

Following the findings in Atanasov, Møller and Priestley (2020) we extract the cyclical component of consumption by employing the linear projection method of Hamilton (2018) which provides a means to identify the cyclical component of a time series. We regress the log of real per capita consumption and investment on a constant and four lagged values of consumption as of date $t-k$:

$$x_t = b_0 + b_1 x_{t-k} + b_2 x_{t-k-1} + b_3 x_{t-k-2} + b_4 x_{t-k-3} + \omega_t, \tag{13}$$

where the regression error, ω_t, is our measure of cyclical component of the series x at time t:

$$cx_t = x_t - \widehat{b}_0 - \widehat{b}_1 x_{t-k} - \widehat{b}_2 x_{t-k-1} - \widehat{b}_3 x_{t-k-2} - \widehat{b}_4 x_{t-k-3}. \tag{14}$$

where x is either consumption or investment and cx is cyclical investment or consumption. Hamilton (2018) provides a discussion of the attractive features of this technique over other popular detrending methods. Following the discussion and analysis in Atanasov, Møller and Priestley (2020) the results we present in the paper are based on cx computed using a horizon of six years, i.e. $k = 24$ with quarterly data which matches well the simulated consumption surplus ratio in Campbell and Cochrane (1999).

Figure 1 shows a time series plot of both detrended cyclical investment, ci, and detrended cyclical consumption, cc. We standardize both variables to ensure compatibility when comparing them and their predictive ability. Cyclical investment has an unconditional mean of zero by construction, a standard deviation of 4.2%, and a first order autocorrelation of 0.96 corresponding to a half-life of slightly over five years. Cyclical consumption which also has an unconditional mean of zero by construction, has a standard deviation of 4.1%, and a

[5] The choice of nondurable consumption folows the work of Kronecke (2017). The results are robust to other measures of aggregate counsumption.

first order autocorrelation of 0.97 also corresponding to a half-life of slightly over five years. Figure 1 reveals that the two series are similar and both series follow business cycle patterns rising in economic expansions and falling in recessions. The correlation coefficient between them is 0.64.

Although we know from simulations in Atanasov, Møller, and Priestley (2020) that the Hamilton filter produces consumption fluctuations that mirror the consumption surplus ratio, it is instructive to compare different detrending methods for reasons of robustness. Therefore, we also detrend with a quadratic time trend model:

$$c_t = d_0 + d_1 t + d_2 t^2 + \omega_t, \tag{15}$$

Figure 2 plots cyclical consumption and cyclical investment using the quadratic detrending method. The two series covary closely together with a correlation coefficient of 0.68. The differences with the Hamilton version are minor with quadratic detrending of consumption producing higher peaks in the early 1970s and during the 2007-2008 financial crisis and lower troughs in the mid 1960s and 1990. Quadratically detrended investment has shorter downturns than the Hamilton detrended consumption. The time series behaviour of detrended investment and consumption with both methods of detrending are similar and distinct from other stock return predictor variables.[6]

The first piece of preliminary evidence that we have is that both investment and consumption fluctuations have a similar time series pattern in that they increase through economic expansions and decrease in recessions. This would appear to suggest that the manager of the firm adjusts investment in line with the consumption decisions of investors.

[6] The correlation with other predictor variables such as the dividend yield and interest rate spreads is low.

4 Predicting Stock Returns

We investigate the forecasting ability of cyclical investment and cyclical consumption for the aggregate stock market excess returns on the Center for Research in Security Prices (CRSP) value-weighted index of U.S. stocks listed on the NYSE, NASDAQ, and Amex. We compute excess returns by subtracting the return on the 30-day Treasury bill from the market return. We use a standard predictive regression model for analyzing aggregate stock return predictability:

$$r^s_{t,t+h} = a_{cc} + b_{cc} * cc_t + u_t \tag{16}$$

where cc_t is one-quarter lagged cyclical consumption and $r^s_{t,t+h}$ is the h-quarter ahead log excess return on the stock market and u_t is the residual. We measure $r^s_{t,t+h}$ as the h-quarter continuously compounded log return on the market less the corresponding h-quarter continuously compounded log Treasury bill return. We also replace cc with investment fluctuations, ci :

$$r^s_{t,t+h} = a_{ci} + b_{ci} * ci_t + v_t \tag{17}$$

In a general equilibrium setting, according to the production model, the manager's investment decisions should mirror the investor's consumption decisions. Therefore, we would expect to see similar sized estimated coefficients on the standardized consumption and investment fluctuations up to a point where arbitrage profits are not possible. Given that we have standardized ci and cc, we then undertake a formal Wald test that $b_{cc} = b_{ci}$. We would also expect to see similar statistical significance and explanatory power. We then repeat the above using the quadratic detrended consumption and investment fluctuations to ensure the results are not simply a consequence of the choice of the detrending method.

Panel A of Table 1 reports the OLS estimates and the corresponding t-statistics which are used to test the significance of the estimated coefficient in equations (16) and (17) using the

Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistic (truncated at lag h; the results are robust towards other choices of truncation lags). We also report the adjusted R^2, $\bar{R}^2$, along with the Wald test that $b_{cc} = b_{ci}$ which is a Chi-squared test with one degree of freedom.

We find that the estimated coefficient on cyclical consumption is negative and that there is an economically sizable predictive impact of cyclical consumption on future excess stock market returns. In particular, the point estimate of b_{cc} in the quarterly regression is -0.015 (second row, second column in Table 1). This represents substantial variation in the risk premium. For example, if cyclical consumption falls by one standard deviation below its mean and hence moves closer to the habit level, expected returns will rise by about six percentage points at an annual rate. The estimate of the coefficient is strongly statistically significant and the associated $\bar{R}^2$ is 3.4%. Thus, expected returns are predicted to be low when consumption is rising above habit in good times or economic upswings, and expected returns are predicted to be high when consumption approaches habit in bad times or economic downturns. This result is consistent with investors who have a habit utility function responding rationally to countercyclical variation in the price of consumption risk over time.

Columns three to eight in Panel A of Table 1 show that predictability extends to longer horizons from 2 quarters to five years. The extent of predictability increases with the horizon both in terms of the size of the estimated coefficients and $\bar{R}^2$ statistics, but at a decreasing rate. For example, at the four quarter horizon the estimated coefficient and $\bar{R}^2$ are almost four times as large as the ones recorded at the one quarter horizon. In contrast, the increase from the sixteenth to the twentieth quarter horizon for the coefficient is small, as is the increase in the $\bar{R}^2$. These results are consistent with those in Atanasov, Møller and Priestley (2020).

The important question that we want to answer is whether the variation in the risk premium that is driven by investor's consumption decisions is matched by manager's investment decisions. Row five of Table 1 reports the estimated coefficients on cyclical investment. At the one quarter horizon the estimate is -0.014 as compared to -0.015 for cyclical consumption. Just as in the case of cyclical consumption, there is a high level of statistical significance. The $\bar{R}^2$ is slightly lower at 0.026 as compared to 0.034. What is clear from these results is that there is a remarkable similarity between the predictability of stock returns from consumption and investment fluctuations. According to the Wald test, it is not possible to reject the null hypothesis that the estimated coefficients are the same. This indicates a very close relationship between investment returns and stock returns as predicted by the production model and as required under general equilibrium. The manager of the firm changes physical investment in a manner that is consistent with the consumption patterns of an investor who exhibits habit in their utility function.

The predictability of stock returns by investment fluctuations continues at longer horizons and matches that of the longer horizon predictability of returns by consumption fluctuations. The statistical significance and explanatory power is a little lower with investment fluctuations. In terms of the comparisons of the size of the estimated coefficients, the eighth row of Panel A of Table 1 reports a Wald test that the estimated coefficients on consumption and investment fluctuations, b_{cc} and b_{ci} are the same, and the ninth row reports the p-values of the test. At all horizons, we are unable to reject the null hypothesis that $b_{cc} = b_{ci}$. At longer horizons, for example the twenty quarter horizon, the estimated coefficients are $b_{cc} = -0.217$ and $b_{ci} = -0.159$ which are economically close, but the p-value of the Wald test falls to 0.07.

In summary, we show that stock returns are predictable to a very similar extent by both cyclical consumption fluctuations and cyclical investment fluctuations at various horizons over the post-war period. It appears that the manager of the firm adjusts the amount of investment in response to variations in the stock market risk premium which will in turn leads to investment returns mirroring stock returns. Expected stock returns are predicted to be high when consumption falls relative to its habit level and cyclical consumption is low and marginal utility is high. In bad times when consumption approaches its habit level the marginal utility of current consumption is high, investors want to consume more and therefore require a higher expected return to give up valuable current consumption. Because of variations in the stock market risk premium, the manger of the firm adjusts the investment decisions. In bad times when the stock market risk premium is predicted to be high, the manager of the firm lowers investment and therefore in the future the marginal rate of transformation is high meaning future investment returns are high. In good times the manger of the firm increases investment driving down the marginal rate of transformation and hence producing lower future investment returns.[7] These findings constitute new evidence that the production model performs well and that investment returns match stock returns over time.

In Panel B of Table 1, we repeat the analysis using the quadratically detrended versions of consumption and investment fluctuations. The predictability of returns is even stronger with these versions and their similarity in predicting returns is now closer. For example, at every horizon except the 20 quarter horizon, we find stronger evidence of predictability with quadratically detrended consumption than with the Hamilton detrended consumption.[8] Overall, Table 1 reveals that there is a very close match between results that regress stock returns on consumption fluctuations and the results that regress stock returns on investment fluctuations. This presents support for the production model.

4.1 Further Tests with Stock Returns

Welch and Goyal (2008) highlight that many business cycle predictor variables have performed particularly poorly after the oil price crisis in the mid 1970s. If there is an economic mechanism that drives the time variation in the risk premium then it should be identifiable over reasonably sized sub samples. This is a weakness with extant predictor variables and has led to the questioning of whether stock returns are predictable in a way that is compat-

[7] This description is consistent with the physical investment future stock return negative relationship among individual firms that is uncovered in the literature (see, for example, Anderson and Garcia-Feijoo (2006), Xing (2008) and Cooper, Gulen, and Schill (2008).

[8] For the remainder of the paper, we only report results using quadratically detreded investment and consumption when there is a noticable difference from the results that use the Hamilton (2018) detrending procedure.

ible with an asset pricing model. However, this inconsistency in predictability should not be present when an economic mechanism such as a habit model or an investment model are the source of time variation in the risk premium. Reasonably sized sub samples that include recessions and expansions should be able to uncover predictability if the predictability is driven by the economic mechanism of an asset pricing model.

To address this point, Table 2 reports the results of stock return predictability for a sample from the first quarter of 1954 to the fourth quarter of 1979 (Panel A) and for a sample from the first quarter of 1980 to the fourth quarter of 2017 (Panel B). In the early sub-sample the estimated coefficients on both consumption fluctuations and investment fluctuations are very similar to each other at all horizons and it is never possible to reject the null hypothesis that the estimated coefficient are equal to one another. These estimates in the first sub-sample are very close to the full sample estimates at all horizons and the explanatory power is around the same.

Panel B of Table 2 reports the results for the second sub-sample. We find that the estimated coefficients on both consumption fluctuations and investment fluctuations are similar across all horizons. The only difference is that the level of statistical significance falls for investment fluctuations at shorter horizons. Inspite of the fall in statistical significance at a few horizons, we can not reject the null hypothesis that $b_{cc} = b_{ci}$.

The analysis across different sub-samples and the comparison with the full sample analysis reveals that there is a remarkable consistency between, first, the size of the estimated coefficient when comparing investment and consumption fluctuations, and second, across periods themselves. Take for example, the one quarter results for the full sample period where the estimated coefficients for consumption fluctuations and investment fluctuations are -0.015 and -0.017 respectively. In the first sub sample they are -0.018 and -0.018, and in the second sub sample they are -0.014 and -0.011 respectively. This consistency in estimates across sub-periods is in sharp contrast to the other stock return predictor variables analyzed in Welch and Goyal (2008). This is important since it suggest that there is a consistent economic mechanism that is driving variation in the risk premium which is consistent with the CCAPM and the production model.

The extant literature shows that some predictor variables are only able to forecast stock returns in bad times as defined by recessions, but not in good times, that is, during business cycle expansions (Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Dangl and Halling (2012), and Golez and Koudijs (2018)). This is a concern because good times are by far the most prevalent times in the data and are periods with low expected returns and consequently these are periods when the manager of the firm should invest. It is quite possible that there are asymmetries in the extent of predictability in good and bad times in terms of the impact a unit of good news has relative to a unit of bad news. However, if it is an economic mechanism that is driving this asymmetry, its impact should still be economically and statistically meaningful in good times as well as bad times. If the production model holds and investment returns are equal to stock returns then we need to see the same estimated coefficient in good and bad times when comparing stock return predictability with consumption fluctuations and investment fluctuations.

To examine whether the relation between future returns and cyclical consumption and cyclical investment is present in both bad and good economic times and whether it is asymmetric across good and bad times, we estimate a linear two-state predictive regression model in the spirit of Boyd, Hu, and Jagannathan (2005):

$$r^s_{t,t+h} = \alpha + \beta_{cc,bad} I_{bad} cc_t + \beta_{cc,good} (1 - I_{bad}) cc_t + \varepsilon_{t,t+h}, \tag{18}$$

where $r^s_{t,t+h}$ is the h-quarter ahead log excess return on the CRSP value-weighted index, I_{bad} is the state indicator that equals one during bad economic states and zero otherwise, and cc_t is one-quarter lagged cyclical consumption. The coefficient $\beta_{cc,bad}$ and $\beta_{cc,good}$ measure the return predictability in bad and good states, respectively. We also estimate

$$r^s_{t,t+h} = \alpha + \beta_{ci,bad} I_{bad} ci_t + \beta_{ci,good} (1 - I_{bad}) ci_t + e_{t,t+h}, \tag{19}$$

where ci_t is one-quarter lagged cyclical investment. We are interested in establishing if $\beta_{ci,bad} = \beta_{cc,bad}$ and $\beta_{ci,good} = \beta_{cc,good}$. Following Dangl and Halling (2012) and Henkel, Martin, and Nardari (2011) we construct the indicator variable I_{bad} by using a value of 1 during the NBER-dated recessions and zero otherwise.

Table 3 presents the results and shows that the predictive power of cyclical consumption provides a consistent description of future stock returns both in good and bad economic states. At the one quarter horizon the coefficient estimate in bad states is four times the size of the coefficient in good states. The difference in the size of coefficients has a substantial economic impact. For example, a one standard deviation fall in cc in bad times leads to an increase in predicted quarterly expected returns of three percentage points. A corresponding change in quarterly returns in good times is just over one percentage point. At horizons of eight quarters or greater, these asymmetric patterns in the estimated coefficients disappear.

We now examine if the manager of the firm also changes the physical investment in bad and good times such that the no arbitrage condition is not broken in bad times and good times. The lower part of Table 3 shows that the pattern of predictive coefficients on investment fluctuations is very similar to that recorded when using consumption fluctuations confirming that the manager of the firm does change investment across good and bad states. For example, at the one quarter horizon, the estimate for consumption fluctuations in good times is -0.011 and for investment fluctuations it is -0.009. In bad times the two estimates are -0.044 and -0.047 respectively. These results show that the manager of the firm does adjust investment asymmetrically in good and bad times in line with how the risk premium changes given the consumption patterns of the investor in good and bad times. These results are worth noting when set into the context of the extant literature which shows that the Welch and Goyal (2008) predictor variables can not predict stock returns in good times. When we predict stock returns with variables that reflect the economic mechanism of two asset pricing models that are consistent with one another, we find that stock returns are predictable equally with each one.

Although consumption fluctuations have a high correlation with investment fluctuations, there are visible difference in Figure 1 and about a third of the variation in consumption and investment fluctuations are independent of one another. If the production model holds and investment returns are equal to stock returns, then the differences in consumption and investment fluctuations should not be able to forecast stock returns, it is only the common element that should be able to forecast stock returns. To test this, Table 4 reports the results from regressing stock returns on the difference between consumption fluctuations and investment fluctuations. We find that all the coefficients at all horizons are very small. There is no other information in consumption fluctuations about future stock returns that is not contained in investment fluctuations, the t-statistics are rarely above 1.0 and the $\overline{R}^2s$ are often negative or very low. These results indicate that we cannot separate investment and consumption fluctuations in terms of the information that they have regarding future stock returns providing further support for the production model.

The results presented so far use consumption measured from durables following the work of Kroneke (2017). We also use personal consumption expenditures (PCE) as the measure of consumption that includes all expenditures on all types of consumption; durables, non-durables, and services. Table 5 reports the estimated coefficients and the Wald test that these estimated coefficients are the same as the estimated coefficients on investment fluctuations that are presented in Table 1. We find that the estimates generated when predicting stocks returns with detrended PCE are even closer to investment fluctuations than when using durables consumption. This is also reflected in the Wald tests where the p-values are greater than 0.5.

Taken together, the evidence presented in this section supports the underlying economic mechanism of the production model that investment returns are equal to stock returns. The estimated coefficients that are a result of regressing stock returns on consumption fluctuations and investment fluctuations are very similar as is the extent of the stock return predictability. These results are robust across sub-samples, good and bad economic times, and using alternative measures of aggregate consumption. We find that differences in investment and consumption fluctuations have no additional predictive power for stock returns, suggesting that the CCAPM and the production model are indeed consistent with one another as shown in Cochrane (1991) and Zhang (2017).

5 Predicting Macroeconomic Quantities

Both employment growth and investment growth can be affected by the risk premium. Lettau and Ludvigson (2002) develop a dynamic version of the q-theory accounting for adjustment cost of investment and derive the result that variations in the risk premium should predict long run investment growth and provide some evidence that investment growth is predictable with the Lettau and Ludvigson (2000) consumption-wealth variable, cay. Chen and Zhang (2011) provide a model with labor adjustment costs that shows that employment growth should be predictable in both the short run and long run by proxies for the risk premium. Møller and Priestley (2020) provide empirical evidence that consumption fluctuations predict both investment and employment growth and this evidence is much stronger and consistent than when predicting with other predictor variables.

It should be the case that if consumption fluctuations can predict macroeconomic quantities, then investment fluctuations should also predict macroeconomic quantities by the same amount if the production model holds. To assess this we estimate:

$$y_{t+1} = \alpha_{cc} + \beta_{cc} * cc_t + \gamma_{cc} y_t + u_t \tag{20}$$

$$y_{t+1} = \alpha_{ci} + \beta_{ci} * ci_t + \gamma_{ci} y_t + v_t \tag{21}$$

where y_{t+1} is investment growth, and employment growth, cc is standardized cyclical consumption, ci is standardized cyclical investment, and u and v are residuals. Give the persistence in macroeconomic variables, we include the first lag of y in the regression. If investment returns are equal to stock returns, we should observe that $\beta_{cc} = \beta_{ci}$ and this can be tested this with a Wald test.

5.1 Investment

Tobin's (1969) Q model of investment predicts an increase (decrease) in investment when the discount rate falls (rises). While this model has failed to be supported in the data, production based models of asset prices that involve frictions in the form of adjustment costs offer an alternative mechanism to help explain investment growth. For example, 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. Lettau and Ludvigson's (2002) 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.

Panel A of Table 6 presents results from predicting investment growth with consumption and investment fluctuations using the Hamilton filter to detrend. With regard to consumption fluctuations, we find predictability of investment growth in line with the empirical results in Møller and Priestley (2020) and the predictions of Lettau and Ludvigson (2002). In particular, a rise in cyclical consumption, indicating a fall in the discount rate, reduces long run investment. The lower part of Panel A shows very similar results using investment fluctuations. The estimate at the one quarter horizon using consumption fluctuations is -0.007 and using investment fluctuations it is -0.008. At the twenty quarter horizon the two estimates are -0.088 and -0.109 for consumption and investment fluctuations respectively. It is never possible to reject the null hypothesis that the coefficient estimates are the same across all horizons.

Panel B of Table 6, which detrends with a quadratic trend, finds very similar results to those in Panel A with the exception that investment growth is more predictable with both consumption fluctuations and investment fluctuations when detrending using the quadratic trend according to both the size of the $\overline{R}^2$ and the extent of the statistical significance of the coefficient estimates. Both Panels A and B of Table 6 confirm that consumption and investment fluctuations have a very similar predictive power for aggregate investment. Irrespective of how consumption and investment are detrended, the size of the estimated coefficients are very similar to each other at any given horizon.

5.2 Employment

Chen and Zhang (2011) derive a novel dynamic model of employment growth. Their insight is 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 increase in employment and a long run decrease in employment. Møller and Priestley (2002) find support for this model when using cyclical consumption.

In Table 7, we test the predictions of the Chen and Zhang's (2011) model that the risk premium can predict employment growth where we proxy the risk premium with both consumption and investment fluctuations. Panel A shows there is evidence of employment growth predictability with the Hamilton method of detrending consumption. At all horizons the estimated coefficients are statistically significant. Comparing these estimates with those that are obtained using investment fluctuations, they are very similar. For example, at the four quarter horizon the estimate for consumption fluctuations is -0.004 and for investment fluctuations it is -0.004. At the twenty quarter horizon the corresponding estimates are -0.040 and -0.024 respectively. There is evidence that predictability is weaker statistically for the Hamilton detrended investment at the eight to sixteen quarter horizons. However, the coefficient estimates are not too far apart and it is not possible to reject the null hypothesis that they are the same.

In Panel B, the results from using quadratic detrending show that the coefficient estimates are very similar across consumption and investment fluctuations, as is their statistical significance and explanatory power. It is never possible to reject the null hypothesis that the coefficient estimates are the same. The statistical significance of the coefficient estimates for both consumption fluctuations and investment fluctuations show that quadratic detrending provides much stronger and consistent evidence of employment growth predictability than the results in Panel A using Hamilton detrending, as was the case for both output and investment predictability. However, the size of the estimated coefficients are similar whether we use the Hamilton or quadratic method of detrending.

Taken together, the results in Table 7 confirm all the earlier findings that consumption fluctuations and investment fluctuations do a very similar job in predicting stock returns and macroeconomic aggregates. This informs us that the proxy for the risk premium from the CCAPM is very similar to that of the production model and suggests that stock returns are the same as investment returns, providing evidence that the economic mechanisms underlying the production model are important in determining the risk premium which in turn is important in determining macroeconomic fluctuations.

6 Conclusion

Recently the q-theory production based asset pricing model has received criticism which has led to calls that its central economic mechanism is flawed and that risk factors that are derived from the model are not actually related to the real economic factors. This is a severe criticism since the workhorse models of empirical asset pricing include factors that are derived from investment and profitability, two central tenants of the production model. However, rejections of the production model in empirical tests should be treated with some caution. The reason for this is that the tests of the production model that have been undertaken have used investment returns which, unlike stock returns, need to be calculated. The calculation of investment returns requires many assumptions, the rejection of any of them could lead to a false rejection of the production model. In essence, to date, we have been faced with a joint hypothesis problem when testing the production model, namely on the one hand the test of the economic mechanism underlying the production model and on the other hand, the many assumptions that are required to calculate investment returns are correct.

This paper uses an insight from a general equilibrium setting to provide a way to test the implications of the production model without the need to calculate investment returns. Instead, we focus on the equivalence of the CCAPM and the production model and note that if stock market expected returns vary over time and that we measure this variation through the consumption surplus of an investor whose utility function exhibits habit formation, then there must be an investment equivalent to the consumption surplus ratio that moves investment returns in the same direction as the manager of the firm alters investment levels in order to make the marginal rate of transformation equal to the marginal rate of substitution. If the production model holds and stock returns are equal to investment returns then the investment equivalent to the consumption surplus ratio should predict not only investment returns but also stock returns the same as the consumption surplus ratio.

We find strong support for the production model. Using detrended consumption which proxies the consumption surplus ratio of Campbell and Cochrane (1999) and equivalently detrended investment, we find that both of these predict stock returns very similarly at all horizons, over different sub samples, in both good and bad economic times, and however we detrend consumption and investment. The results are robust to different measures of consumption and there is no additional information in detrended consumption that is not included in detrended investment. Our results using stock returns support the equivalence between the CCAPM and the production model as encapsulated in a general equilibrium framework. We also find that investment and employment are predictable in a very similar way when using both detrended consumption and detrended investment. This suggests that both of these are similar proxies for the equity market risk premium that drives macroeconomic quantities. Side stepping the need to calculate investment returns, our results provide support for the role of the economic mechanisms that underlying both the CCAPM and the production model. These findings indicate that refining ways to calculate investment returns is likely to be a fruitful avenue for future research.

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Table 1
Predicting Stock Returns

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cx_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter ahead log stock market return, and cx_t is one-quarter lagged cyclical consumption, cc, or one quarter lagged cyclical investment, ci. The table shows results for excess market returns on the CRSP value-weighted index. For each regression, the table reports the slope estimate, Newey-West corrected t-statistics in parentheses (h lags), and adjusted R^2 statistics, ARsqd. Chi-sq is a Wald test that the coefficient estimate on cc is equal to the coefficient on ci. Panel A reports results using the Hamilton detrending methodology and Panel B uses the Quadratic detrending methodology. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Hamilton Trend

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc	-0.015	-0.030	-0.059	-0.104	-0.136	-0.182	-0.217
t-stat	-3.189	-3.646	-3.953	-4.133	-4.575	-5.657	-6.135
ARsqd	0.034	0.063	0.126	0.223	0.292	0.412	0.437
ci	-0.014	-0.025	-0.042	-0.064	-0.093	-0.131	-0.159
t-stat	-2.741	-2.787	-2.439	-2.157	-2.956	-4.703	-4.936
ARsqd	0.026	0.042	0.061	0.082	0.134	0.214	0.245
Chi-sq	0.126	0.335	1.035	1.804	1.868	3.336	3.295
p-value	0.722	0.563	0.309	0.179	0.172	0.068	0.069

Panel B: Quadratic Trend

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cq	-0.017	-0.034	-0.066	-0.119	-0.148	-0.182	-0.200
t-stat	-3.844	-3.845	-3.682	-4.295	-5.519	-6.155	-4.913
ARsqd	0.044	0.080	0.158	0.291	0.348	0.414	0.388
iq	-0.016	-0.030	-0.053	-0.085	-0.122	-0.154	-0.169
t-stat	-3.193	-3.263	-3.050	-3.063	-4.300	-5.081	-4.566
ARsqd	0.035	0.061	0.099	0.145	0.231	0.298	0.281
Chi-sq	0.115	0.202	0.577	1.458	0.864	0.833	0.717
p-value	0.734	0.653	0.447	0.227	0.353	0.361	0.397

Table 2

Sub-Sample Analysis

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cx_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter ahead log stock market return, and cx_t is one-quarter lagged cyclical consumption, cc, or one quarter lagged cyclical investment, ci. The table shows results for excess market returns on the CRSP value-weighted index. For each regression, the table reports the slope estimate, Newey-West corrected t-statistics in parentheses (h lags), and adjusted R^2 statistics, ARsqd. Chi-sq is a Wald test that the coefficient estimate on cc is equal to the coefficient on ci. Panel A reports results for the sample period 1954Q1 to 1979Q4. Panel B uses the sample period 1980Q1 to 2017q4.

Panel A: 1954:1 - 1979:4

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc	-0.018	-0.033	-0.063	-0.091	-0.101	-0.147	-0.205
t-stat	-2.129	-2.375	-2.490	-2.441	-3.298	-5.283	-5.443
ARsqd	0.044	0.069	0.139	0.182	0.238	0.450	0.557
ci	-0.018	-0.033	-0.053	-0.062	-0.068	-0.117	-0.175
t-stat	-2.413	-2.384	-2.252	-2.017	-2.525	-5.749	-5.821
ARsqd	0.041	0.064	0.092	0.075	0.096	0.271	0.394
Chi-sq	0.000	0.000	0.159	0.869	1.531	2.026	0.988
p-value	1.000	0.987	0.690	0.351	0.216	0.155	0.320

Panel B: 1980:1 - 2017:4

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc	-0.014	-0.029	-0.057	-0.114	-0.158	-0.203	-0.221
t-stat	-2.505	-2.869	-3.065	-3.254	-3.613	-4.393	-4.301
ARsqd	0.024	0.056	0.116	0.254	0.339	0.429	0.405
ci	-0.011	-0.021	-0.036	-0.071	-0.116	-0.146	-0.155
t-stat	-1.734	-1.828	-1.563	-1.607	-2.578	-3.508	-3.146
ARsqd	0.014	0.028	0.044	0.097	0.181	0.228	0.217
Chi-sq	0.160	0.454	0.795	0.945	0.882	1.888	1.779
p-value	0.689	0.500	0.373	0.331	0.348	0.169	0.182

Table 3

Predicting Stock Returns in Good and Bad Times

The table presents results of two-state predictive regressions of the form $r_{t,t+h} = \alpha + \beta_{cc,bad} I_{bad} cc_t + \beta_{cc,good} (1 - I_{bad}) cc_t + \varepsilon_{t,t+h}$, and $r_{t,t+h} = \alpha + \beta_{ci,bad} I_{bad} ci_t + \beta_{ci,good} (1 - I_{bad}) ci_t + \varepsilon_{t,t+h}$,where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter ahead log excess return on the CRSP value-weighted index, cc_t is one-quarter lagged cyclical consumption, ci_t is one-quarter lagged cyclical investment, and I_{bad} is the state indicator that equals one during bad economic states and zero otherwise. We employ the NBER-dated chronology of recessions to define bad states following Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011). For each regression, the table reports the slope estimate, Newey-West corrected t-statistics in parentheses (h lags), and adjusted R^2 statistics, ARsqd. The sample covers the period from 1954Q1 to 2017Q4.

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc good	-0.011	-0.024	-0.048	-0.105	-0.141	-0.181	-0.218
t-stat	-2.354	-2.843	-3.331	-4.100	-4.342	-5.073	-5.514
cc bad	-0.044	-0.073	-0.130	-0.100	-0.107	-0.186	-0.210
t-stat	-2.312	-2.274	-2.311	-1.593	-2.455	-5.074	-4.501
ARsqd	0.051	0.081	0.152	0.219	0.291	0.409	0.435
ci good	-0.009	-0.019	-0.032	-0.060	-0.093	-0.134	-0.163
t-stat	-1.681	-1.972	-1.805	-1.825	-2.598	-4.465	-5.292
ci bad	-0.047	-0.068	-0.107	-0.095	-0.095	-0.109	-0.132
t-stat	-3.276	-3.018	-2.479	-1.774	-2.011	-1.632	-1.427
ARsqd	0.049	0.059	0.081	0.081	0.131	0.212	0.243

Table 4

Difference in Consumption and Investment Fluctuations

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta(cc - ci)_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter ahead log stock market return, and cc_t is one-quarter lagged cyclical consumption and ci is one quarter lagged cyclical investment. The table shows results for excess market returns on the CRSP value-weighted index. For each regression, the table reports the slope estimate, Newey-West corrected t-statistics in parentheses (h lags), and adjusted R^2 statistics, ARsqd. The sample covers the period from 1954Q1 to 2017Q4.

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc-ci	-0.002	-0.007	-0.024	-0.056	-0.060	-0.067	-0.065
t-stat	-0.432	-0.736	-1.315	-1.433	-1.146	-1.105	-0.974
ARsqd	-0.003	-0.001	0.012	0.043	0.037	0.038	0.026

Table 5

Alternative Consumption Measures

The table presents results of predictive regressions of the form $r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h}$, where h denotes the horizon in quarters, $r_{t,t+h}$ is the h-quarter ahead log stock market return, and ccx_t is one-quarter lagged cyclical consumption measured as aggregate personal consumption expenditures. The table shows results for excess market returns on the CRSP value-weighted index. For each regression, the table reports the slope estimate, Newey-West corrected t-statistics in parentheses (h lags), and adjusted R^2 statistics, ARsqd. Chi-sq is a Wald test that the coefficient estimate on cc is equal to the coefficient on ci that is presented in Panel A of Table 1. The sample covers the period from 1954Q1 to 2017Q4.

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc	-0.012	-0.024	-0.045	-0.083	-0.110	-0.143	-0.174
t-stat	-3.009	-3.292	-3.420	-4.147	-4.634	-4.772	-4.643
ARsqd	0.031	0.057	0.110	0.209	0.284	0.376	0.414
Chi-sq	0.104	0.024	0.050	0.393	0.292	0.184	0.218
p-value	0.747	0.877	0.823	0.531	0.589	0.668	0.640

Table 6

Predicting Investment Growth

The table presents results of predictive regressions, $\Delta i_{t+h} = i_{t+h} - i_t = a_0 + a_1 cc_t + a_2 \Delta i_t + v_{t+h}$, where $\Delta i_{t+h} = i_{t+h} - i_t$ is h-period ahead log growth in investment and cx_t is either cyclical consumption, cc, or cyclical investment, ci. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic, ARsqd. Panel A reports results using the Hamilton detrending methodology and Panel B uses the Quadratic detrending methodology. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Hamilton Trend

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc	-0.002	-0.005	-0.014	-0.032	-0.048	-0.064	-0.088
t-stat	-1.731	-2.224	-2.619	-2.987	-2.819	-2.603	-3.588
i	0.566	0.492	0.194	-0.165	-0.215	-0.106	0.044
t-stat	9.304	6.982	2.373	-1.558	-1.576	-0.820	0.368
ARsqd	0.324	0.251	0.071	0.136	0.249	0.299	0.378
ci	-0.002	-0.007	-0.017	-0.022	-0.023	-0.043	-0.109
t-stat	-2.475	-2.987	-2.613	-1.532	-1.155	-1.539	-4.504
i	0.579	0.524	0.259	-0.100	-0.173	-0.028	0.436
t-stat	9.637	7.400	2.901	-0.813	-1.008	-0.134	2.716
ARsqd	0.330	0.270	0.087	0.068	0.106	0.126	0.228
Chi-sq	0.653	0.957	0.217	0.585	1.515	0.520	0.780
p-value	0.419	0.328	0.641	0.444	0.218	0.471	0.377

Panel B: Quadratic Trend

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cq	-0.001	-0.005	-0.016	-0.042	-0.066	-0.083	-0.094
t-stat	-1.598	-2.112	-2.443	-3.104	-4.153	-5.235	-5.558
i	0.570	0.501	0.215	-0.141	-0.211	-0.152	-0.115
t-stat	9.406	7.141	2.649	-1.433	-1.762	-1.458	-1.062
ARsqd	0.323	0.254	0.088	0.213	0.406	0.512	0.543
iq	-0.004	-0.012	-0.031	-0.060	-0.084	-0.112	-0.139
t-stat	-4.291	-4.682	-4.392	-4.288	-4.464	-5.296	-8.992
i	0.586	0.551	0.342	0.109	0.141	0.306	0.450
t-stat	9.831	8.167	3.928	0.892	0.814	1.798	4.711
ARsqd	0.352	0.332	0.224	0.299	0.422	0.547	0.667
Chi-sq	7.100	6.617	4.156	1.602	0.942	1.805	8.557
p-value	0.008	0.010	0.041	0.206	0.332	0.179	0.003

Table 7

Predicting Employment Growth

The table presents results of predictive regressions, $\Delta e_{t+h} = e_{t+h} - e_t = a_0 + a_1 cc_t + a_2 \Delta e_t + u_{t+h}$, where $\Delta e_{t+h} = e_{t+h} - e_t$ is h-period ahead log growth in employment and cx_t is either cyclical consumption, cc, or cyclical investment, ci. For each regression, the table reports the slope estimate, the Newey-West corrected t-statistic (h lags), and the adjusted R^2 statistic, ARsqd. Panel A reports results using the Hamilton detrending methodology and Panel B uses the Quadratic detrending methodology. The sample covers the period from 1954Q1 to 2017Q4.

Panel A: Hamilton Trend

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cc	-0.000	-0.002	-0.004	-0.010	-0.017	-0.028	-0.040
t-stat	-2.118	-2.576	-2.545	-2.446	-2.540	-2.955	-4.034
e	0.735	0.602	0.355	0.128	0.139	0.280	0.453
t-stat	11.400	6.816	3.175	0.935	0.780	1.280	2.064
ARsqd	0.546	0.366	0.138	0.083	0.159	0.280	0.426
ci	-0.001	-0.002	-0.004	-0.007	-0.010	-0.015	-0.024
t-stat	-2.646	-2.840	-2.402	-1.562	-1.445	-1.874	-2.526
e	0.742	0.619	0.386	0.140	0.112	0.204	0.344
t-stat	11.568	6.995	3.276	0.962	0.662	1.002	1.323
ARsqd	0.550	0.373	0.139	0.028	0.033	0.067	0.126
Chi-sq	0.434	0.199	0.015	0.554	1.379	2.199	3.191
p-value	0.510	0.656	0.902	0.457	0.240	0.138	0.074

Panel B: Quadratic Trend

	h=1	h=2	h=4	h=8	h=12	h=16	h=20
cq	-0.000	-0.002	-0.005	-0.014	-0.022	-0.031	-0.038
t-stat	-2.427	-2.868	-2.728	-3.094	-3.785	-4.953	-5.200
e	0.739	0.612	0.376	0.156	0.138	0.207	0.261
t-stat	11.558	6.939	3.368	1.230	0.990	1.465	1.796
ARsqd	0.548	0.372	0.160	0.169	0.299	0.435	0.504
iq	-0.001	-0.003	-0.008	-0.018	-0.026	-0.033	-0.038
t-stat	-3.827	-4.358	-4.250	-4.126	-4.328	-4.475	-4.762
e	0.737	0.623	0.437	0.299	0.295	0.324	0.362
t-stat	11.642	7.288	3.948	2.097	1.775	1.883	1.904
ARsqd	0.563	0.419	0.261	0.270	0.344	0.415	0.475
Chi-sq	2.780	3.112	2.688	1.188	0.410	0.028	0.004
p-value	0.095	0.078	0.101	0.276	0.522	0.868	0.950

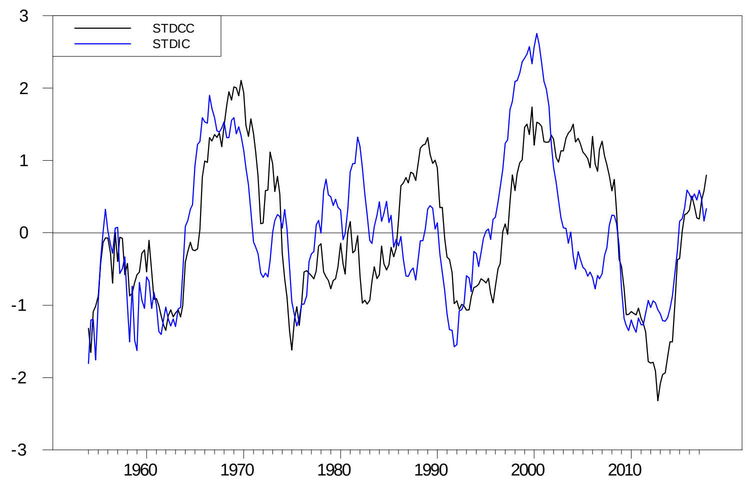

Figure 1: This figure plots standardized consumption fluctuations (STDCC) and standardized investment fluctutations (STDIC) detrended by the Hamilton method. The data are plotted over the sample period 1954Q1 to 2017Q4. Consumption in measured as consumption of non-durables. Investment is total non-residential investment.

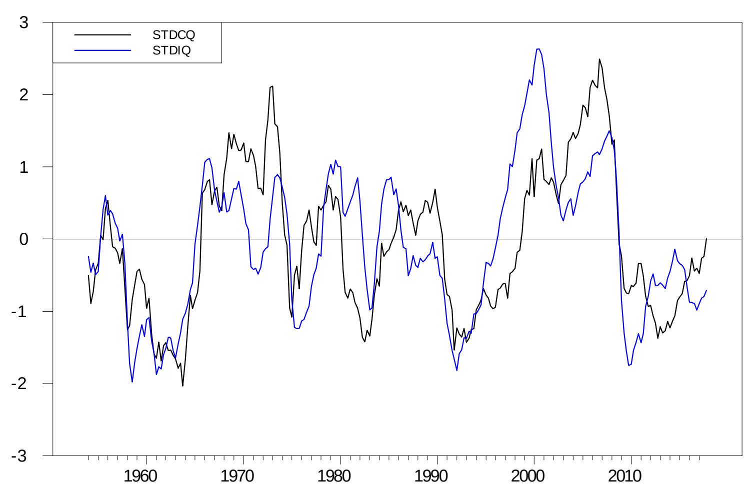

Figure 2: This figure plots standardized consumption fluctuations (STDCC) and standardized investment fluctutations (STDIC) detrended by a liner and quadratic trend. The data are plotted over the sample period 1954Q1 to 2017Q4. Consumption in measured as consumption of non-durables. Investment is total non-residential investment.