Putty-Clay Technology and Stock Market Volatility

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Abstract

I derive a production-based asset pricing formula to infer aggregate stock market returns from macroeconomic time series when the technology is putty-clay. Capital heterogeneity leads to variation in the aggregate stock market value through a new compositional effect. The asset pricing formula, which holds regardless of the stochastic discount factor, predicts that the stock market value is high when the ratio of investment to gross job creation is low. This contrasts with the adjustment cost model which predicts that the stock market value is high when the investment-capital ratio is high. Incorporating the putty-clay technology substantially increases the ability of the adjustment cost model to match the data on U.S. stock returns.

1 Introduction

While much interest in macroeconomics has been devoted to asset pricing puzzles, most of this work is limited to endowment economies. Production economies present additional challenges for macroeconomics. In the standard stochastic growth model, the price of capital (i.e. marginal Tobin's q) is constant, and equal to one, because consumption goods can always be transformed into capital goods one-for-one. Hence, the value of a firm equals its quantity of capital. Equivalently, the return on capital is the current period marginal product minus the depreciation rate. This model has wildly counterfactual predictions: the return on capital from the model is two orders of magnitude less volatile than the empirical stock market return (Rouwenhorst (1995)).

The standard response to this empirical challenge is to assume adjustment costs. These introduce a wedge between the value of installed capital and the value of consumption goods. If adjustment costs are steep enough, variations in investment can create large variations in the value of installed capital (see Hayashi (1982), Cochrane (1991), Jermann (1998), and Hall (2001)). However, the adjustment cost model raises several empirical issues. First, the curvature of the adjustment cost function needs to be high to match the volatility of the stock market. Second, the stock return implied by the adjustment cost model systematically lags the empirical stock return. Third, large adjustment costs, when embedded in a standard real business cycle model, lead to counterfactual business cycle implications: employment becomes countercyclical (Jermann (1998), Boldrin, Christiano and Fisher (2001)). Finally, it is unclear how to reconcile the high curvature of adjustment costs with microeconomic evidence which does not point towards large, smooth adjustment costs (Cooper and Haltiwanger (2006)). All of this led Robert Hall to favor a lower estimate of adjustment costs in his work on intangibles (2001), and to argue later (2004) that "rents arising from adjustment costs are relatively small and are not an important part of the explanation of the large movements of the values of corporations".

The contribution of my paper is to study, theoretically and empirically, the aggregate asset pricing implications of a putty-clay technology: I find that it provides an appealing alternative to the adjustment cost technology. With the putty-clay technology, pieces of equipment ("machines") differ in capital intensity. Capital intensity is chosen once and for all at the time of investment. For instance, an aircraft requires exactly two pilots; or a computer workstation will be used by one person. Ex-ante, it is possible to choose a higher or lower capital intensity, but ex-post it is fixed. Picking a high capital intensity requires a higher investment upfront and reduces future labor costs per unit of output.

The value of a firm now is a function not only of the quantity of capital that it has, but also of the characteristics of that capital (i.e., of its capital intensity). This leads to a new channel which creates return volatility. When a productivity shock hits the economy, different machines react differently. Intuitively, in good times, having more quantity of capital (more productive capacity) is valuable since prices are high and profits per unit of capacity are high. On the other hand, productive capacity is much less valuable in bad times since prices are low. But having a low cost of production is almost equally valuable in bad and good times since this increases the profit per unit. Hence, the relative advantage of having a low cost is higher in bad times - that is, low-capital intensity capital is more procyclical than high-productivity capital.[1]

To find the aggregate effect of a productivity shock on the stock market, one must sum the effects on all the machines using the cross-sectional distribution. If there is trend growth in the economy, old, low capital-intensity machines represent a large share of the capital stock and their responses dominate the ones of highly productive machines. This in turn makes the aggregate stock market procyclical as low productivity machines are more responsive to aggregate

[1] This discussion is easier to give in terms of prices; of course, in a macroeconomic model the price of the good is the numeraire. Saying that in good times the price is high is equivalent to saying that the real wage is relatively low relative to productivity. Hence, my analysis relies on the stylized fact that wages are smooth.

productivity shocks. Importantly, the key difference between capital goods is their productivity. For simplicity I concentrate on differences in capital intensity, but vintage effects or idiosyncratic productivity could also be important.

The model's results are captured by a key variable: the optimal capital intensity of new investment i_t (i.e., the ratio of aggregate investment to gross job creation). The model's implications are closer to the data when this variable is volatile and countercyclical. Intuitively, when the stock market value goes up, investments with a lower capital intensity become more valuable. This gives investors an incentive to choose a lower capital intensity. Thus the model predicts that stock market values and i_t are negatively correlated.

The empirical section shows that in the data, the variable i_t is indeed volatile and countercyclical, so that the model generates substantial volatility in prices. The putty-clay model alone fits the return data reasonably well; but, interestingly, I find that the best model incorporates both putty-clay and adjustment cost features, each accounting for roughly 50% of total volatility. Moreover, the putty-clay model helps explain some specific features of the data, including the fact that the stock market return leads GDP growth.

Besides theoretically characterizing and empirically evaluating this channel for price variation, an important contribution of the paper is the provision of a simple framework with which to study putty-clay technology. There has been relatively little work in this area due to the intractability of the model: the endogenous, time-varying cross-sectional distribution of production units must be computed as part of solving for the equilibrium, which generates a curse of dimensionality. In contrast, my paper adds a single additional state variable to the standard neoclassical growth model.

The rest of the paper is organized as follows: Section 2 describes the model, Section 3 derives its theoretical implications, and Section 4 examines these implications empirically.

2 A putty-clay model

The putty-clay technology makes a distinction between short-run and long-run elasticities of substitution between capital and labor: installed capital has a fixed labor requirement, and substitution is feasible only through the purchase of new equipment.[2] In the long-run, one obtains

[2] There is also a utilization margin however: one can change the number of hours the equipment is used. But in many instances, the equipment is usually running at full capacity: commercial airplanes fly nearly continuously, and most colleges cannot accomodate more students easily. Even when the equipment is running at less than full

the standard unit elasticity of substitution, which guarantees that the labor share of national income exhibits no long-run trend.

The technology I use is a simplification of the putty-clay formulation introduced by Gilchrist and Williams (2000) to study business cycles. It is also closely related to the setup Atkeson and Kehoe (1999) used to study energy demand.[3] The Gilchrist and Williams (2000) model suffers from a curse of dimensionality, while my model has requires adding only one state variable to the benchmark neoclassical growth model.

A. Technology

Production occurs in a continuum of production units called *machines*. For clarity, think of a representative firm as creating new machines each period, adding them to the existing stock, operating them, paying wages, and rebating dividends to households. To build a machine, the firm chooses its capital intensity, or capital per worker, which is denoted i. These machines have constant returns to scale so I can normalize them to have one worker, and hence i is also the total amount of capital put into the machine (i.e. its construction cost). Once i is chosen, it remains fixed forever. One can view this as a "quality-quantity" trade-off in the choice of capital: the firm can choose between a small number of highly capital intensive machines or a large number of low capital intensity machines. As usual, the machines built today come into operation in the following period.

The output of a machine is $y(n) = Ai^{\alpha} \times \min(n, 1)$, where A is current aggregate productivity, n current employment, and α is the long-run capital share. From now on, I refer to A as TFP (but it is not the standard Solow residual). As this equation shows, a machine can operate at full capacity with one worker ($n = 1$), or it can operate at less than full capacity ($n < 1$). This output per worker is the usual Cobb-Douglas production function, since i is the capital per worker. Once a machine is built it has no scrap value: investment is irreversible. Machines have a constant probability δ of breaking down each period: hence depreciation here is a matter of machines

capacity, it may be costly to vary utilization (e.g. to organize a night shift, or to train additional workers).

[3] Other recent work using a putty-clay technology includes Franco (2003), Gilchrist and Williams (2000b, 2004), and Wei (2003). Wei's paper is the most closely related to this paper. Her model extends the putty-clay model of Gilchrist and Williams to incorporate energy. She uses the full DSGE model to compute the effect of an increase in oil prices on the value of existing firms. The effect is small, despite the size of shock, because oil expenditure is a small share of output, and because of a reduction of the real wage in general equilibrium. In my model, the effects are larger because the share of labor in expenditures is large (but the putty-clay assumption may be less realistic than for energy).

disappearing, not of machines shrinking in size.

I now make an important simplification to the Gilchrist and Williams setup by requiring machines to operate at full capacity as long as they have not broken down, i.e., to always set $n = 1$. One can think of this as a technological or regulatory constraint on machines. But actually, this assumption would be a true result if, along the equilibrium path, the operating profit of any existing machine were positive: $\pi(A, i, w) = Ai^\alpha - w \geq 0$ for all existing i's, where w denotes the aggregate wage, so that owners *choose* to operate machines at full capacity. This turns out to be almost the case for some parameter values, in the following sense: in any given period some very low capital-intensity machines (i.e. which where built with a low i, generally the older ones) may not satisfy these conditions; however, because of depreciation there will be very few of these machines. This assumption is a very convenient shortcut both for theoretical and numerical analysis. An appendix to this paper compares the results from this model with the results from the model with variable utilization (i.e., the Gilchrist-Williams model). I find that both prices and quantities behave similarly in the two models; the main difference is that employment is less cyclical in my model.

B. Aggregation

I can now find the law of motion for the number of machines of each capital intensity. Let h_t be the number of new machines built at time t, which is also the gross creation of jobs at time t since each machine has one job. Let i_t be the capital intensity which is chosen at time t. (Since all machines are identical ex-ante, and investors have the same information, they choose to build machines with the same capital intensity at time t.) The law of motion for the measure G_t of machines with capital intensity less than i is:

$$\forall i \geq 0 : G_{t+1}(i) = (1 - \delta)G_t(i) + h_t \mathbf{1}_{i \geq i_t}, \tag{2.1}$$

so that the number of machines of capital intensity less than i at time $t + 1$ is the number of machines of capital intensity less than i at time t that did not depreciate, plus the new machines: these were designed in quantity h_t with capital intensity i_t, whence the step function $\mathbf{1}_{i \geq i_t}$.

Total output in this economy is obtained by summing output across machines, $Y_t = \int_0^\infty A_t i^\alpha dG_t(i) = A_t \int_0^\infty i^\alpha dG_t(i)$. Let $\overline{Y}_t = \int_0^\infty i^\alpha dG_t(i)$, be the "productive capacity" of the economy, and notice that this part of output is predetermined. Total employment is $\overline{N_t} = \int_0^\infty dG_t(i)$ since there is one job per machine. Hence labor demand is predetermined too, given our assumption that machines operate at full capacity.

Aggregate investment I_t is the product of the number of new machines h_t and the units of capital per machine $i_t : I_t = i_t h_t$. The resource constraint of the economy is

$$C_t + I_t \leq Y_t. \tag{2.2}$$

Since the results given in this paper do not directly assume anything about preferences, this resource constraint is not exploited in my analysis.

C. Law of motion for the endogenous state variables

Clearly, the distribution $G_t(.)$ is relevant for aggregates only through its two moments $\overline{Y}_t = \int_0^\infty i^\alpha dG_t(i)$ and $\overline{N}_t = \int_0^\infty dG_t(i)$. I can obtain simple law of motions for these two moments from the law of motion for $G_t(.)$:

$$\begin{aligned} \overline{Y}_{t+1} &= \int_0^\infty i^\alpha dG_{t+1}(i), \\ &= \int_0^\infty i^\alpha \left((1-\delta)dG_t(i) + h_t \boldsymbol{\varepsilon}_{i=i_t}\right) \\ &= (1-\delta)\overline{Y}_t + h_t i_t^\alpha, \end{aligned} \tag{2.3}$$

where $\boldsymbol{\varepsilon}_{x=x_0}$ denotes a Dirac distribution (a unit mass) at point x_0. Similarly,

$$\begin{aligned} \overline{N}_{t+1} &= \int_0^\infty dG_{t+1}(i) \\ &= \int_0^\infty \left((1-\delta)dG_t(i) + h_t \boldsymbol{\varepsilon}_{i=i_t}\right) \\ &= (1-\delta)\overline{N}_t + h_t. \end{aligned} \tag{2.4}$$

These equations are easy to interpret: equation (2.4) says that employment (the number of jobs) at time $t+1$ equals the number of jobs at time t, $\overline{N}_t$, minus jobs destroyed $\delta\overline{N}_t$, plus the new jobs h_t created at time t, which come into line at time $t+1$. Equation (2.3) similarly says that the new productive capacity $\overline{Y}_{t+1}$ equals undepreciated capacity $(1-\delta)\overline{Y}_t$ plus the capacity of new machines, i.e. the product of the number of new machines, times the productivity of each of the new machines.

The key point is that I can express the two endogenous state variables $\overline{Y}_{t+1}$ and $\overline{N}_{t+1}$ as a function of their own lags $\overline{Y}_t$ and $\overline{N}_t$. This is precisely the reason why no "curse of dimensionality" arises in my model, in contrast to the Gilchrist and Williams (2000) model. In the standard neoclassical growth model, the only state variable is the quantity of capital K_t; in my model, the two state variables are the number of production units $\overline{N}_t$ and the total output they produce $\overline{Y}_t$.

These variables capture the quantity as well as the average productivity of the existing stock of machines.

Because my results do not depend on preferences, I do not need to close the model. This is attractive given that the empirical finance literature has not reached a definite conclusion regarding what the correct stochastic discount factor (i.e., aggregate utility function) should be. But it is important to note that it is straightforward to extend this model to general equilibrium, by positing a representative consumer who maximizes an expected discounted time-separable utility function of consumption and labor and specifying a stochastic process for TFP A_t.[4]

3 The theoretical link between stock returns, investment, and job creation

This section derives the production-based formula for the value of the capital stock of the model economy. The value is a simple function of some macroeconomic variables: $V_t = g\left(i_t, \overline{Y}_t, \overline{N}_t\right)$. The first step to obtain this formula is to analyze the investment problem of the representative firm and to calculate the value of a given machine. The second step is to aggregate across the existing stock of machines to find the total stock market value. The third step is to finally analyze the implications of this formula.

A. Investment decision

Given the assumption of full utilization exogenous exit, there is no decision to make regarding existing machines: they simply generate cash flows which depend on TFP and wages. The only interesting margin is new machines - how many to build, and which capital intensity to choose for each machine. These decisions are driven by value maximization. The value of an installed production unit is the present discounted value of cash flows, given expected realizations of TFP A_{t+s} and wages w_{t+s} as well as discount rates $m_{t,t+s}$ (i.e., the stochastic discount factor). Mathematically, the ex-dividend value of a machine of capital intensity i is:

$$P_t(i) = E_t \sum_{s \geq 1} m_{t,t+s} (1-\delta)^{s-1} \left(A_{t+s} i^{\alpha} - w_{t+s}\right).$$

This present value can be broken down into two terms, the present value of revenues and the present value of costs:

$$P_t(i) = q_{A,t} i^{\alpha} - q_{w,t}, \tag{3.1}$$

[4] The DSGE version can be simply solved using the social planner problem: choose contingent plans for $\{c_t, i_t, h_t\}$ to maximize utility subject to the constraints (2.2), (2.3), (2.4), and an initial condition $(\overline{Y}_0, \overline{N}_0)$.

where $q_{A,t} \overset{def}{=} E_t \sum_{s\geq 1} m_{t,t+s}(1-\delta)^{s-1}A_{t+s}$ and $q_{w,t} \overset{def}{=} E_t \sum_{s\geq 1} m_{t,t+s}(1-\delta)^{s-1}w_{t+s}$ are the present discounted values of TFP and wages respectively.

I now use this expression to analyze the choice of capital intensity i and the choice of the number of new machines produced each period. First, let's examine the choice of capital intensity for a given machine. The firm chooses i_t to maximize the value, net of the real creation cost i, so the optimal choice of i at time t is obtained as the solution to the program

$$\max_{i\geq 0} \{P_t(i) - i\}. \tag{3.2}$$

Given (3.1), this program is strictly concave and its solution is characterized by the first-order condition:

$$\frac{i_t^{1-\alpha}}{\alpha} = q_{A,t}. \tag{3.3}$$

Hence, given the expected realizations of TFP, wages and discount rates, there is a unique optimal capital intensity i_t at time t, and the economy produces new machines of only this capital intensity.

There is also a free-entry condition that equates the value of a new machine and the cost of building it:

$$P_t(i_t) = i_t, \tag{3.4}$$

which, given the value formula (3.1), leads to:

$$i_t^{\alpha} q_{A,t} - q_{w,t} = i_t. \tag{3.5}$$

There are no adjustment costs along this margin: with the replacement cost of capital equal to the value of capital, Tobin's q is equal to one for these new machines. (However, at the machine level adjustment costs are infinite since capital cannot be changed.) For machines with a capital intensity different from i_t, Tobin's q is less than one since the irreversibility constraint binds.

Given the conditions (3.3) and (3.5), I can solve for $q_{A,t}$ and $q_{w,t}$ as a function of one single endogenous variable i_t:

$$q_{A,t} = \frac{i_t^{1-\alpha}}{\alpha}, \tag{3.6}$$

$$q_{w,t} = \frac{1-\alpha}{\alpha} i_t. \tag{3.7}$$

The key variable in the model is i_t, the capital intensity of new investment. It is chosen at the time of investment to minimize expected discounted costs, which depend on future interest rates, TFP, and wages. For instance, choosing a low i_t implies that you invest less initially, but that you rely more on labor, and thus have higher operating costs. A low i_t thus reflects a choice towards more capacity and higher costs. Of course, in a full general equilibrium i_t is endogenously determined by expectations of wages, interest rates and productivity; but i_t turns out to be a sufficient statistic for asset prices.

B. The value of the aggregate stock market

The ex-dividend value of the aggregate stock market V_t is found by summing the values of all the machines in the economy:

$$\begin{aligned} V_t &= \int_0^\infty P_t(i) dG_t(i) \\ &= \int_0^\infty \left(q_{A,t} i^\alpha - q_{w,t}\right) dG_t(i) \\ &= q_{A,t} \overline{Y}_t - q_{w,t} \overline{N_t}, \end{aligned}$$

where the second line uses (3.1) and the third line uses the definitions $\overline{Y}_t = \int_0^\infty i^\alpha dG_t(i)$ and $\overline{N_t} = \int_0^\infty dG_t(i)$.

Using the expressions (3.6-3.7) derived in the preceding section for $q_{A,t}$ and $q_{w,t}$, I obtain:

Result 1: The value of the stock market is

$$V_t = \frac{i_t}{\alpha} \left(\frac{\overline{Y}_t}{i_t^\alpha} - (1-\alpha) \overline{N}_t \right) \overset{def}{=} g(i_t, \overline{Y}_t, \overline{N}_t). \tag{3.8}$$

This is the central formula of the paper. It links the value of the stock market V_t with macroeconomic variables. The value of existing machines is the present discounted value of future cash flows (i.e., the present value of the future output that these machines will produce, minus the labor costs they will require). The present value of future costs and output are summarized by the variable i_t.

It is interesting to compare this formula with its counterpart in the standard neoclassical growth model. If there are no adjustment costs, $V_t = K_t$: the value of the stock market is predetermined, and it moves only by the amount of the change in the real quantity of capital. This is clearly at odds with the empirical volatility of the aggregate stock market. The standard answer to this limitation of the model is to introduce an adjustment cost, so that this expression becomes $V_t = q_t K_t$ where q_t is Tobin's q, an increasing function of the investment-capital ratio. In this case, variation in q_t leads to price variation.

Formally, equation (3.8) yields a similar implication: since i_t is a jump (or control) variable, the stock market value is not predetermined, even though the quantities of the various types of capital - the distribution $G_t(i)$ - are. Hence, this theory generates some volatility in the price of capital, even though there are no adjustment costs in the creation of new machines. A change in the optimal type (capital intensity) of new capital i_t alters the value of the existing capital stock. More precisely, since $\overline{Y}_t$ and $\overline{N_t}$ are predetermined state variables, any instantaneous impact on the value of capital must go through i_t, the only jump (or control) variable in (3.8). Hence the conditional volatility of the stock market value is directly related to the conditional volatility of i_t.

But is it a low or high i which is associated with an increase in stock prices? To find out, I compute $\partial g/\partial i$. Its sign depends on endogenous state variables, but I can evaluate this expression at the nonstochastic steady-state. First, a direct computation gives

$$\frac{\partial g(i,\overline{Y},\overline{N})}{\partial i} = \frac{1-\alpha}{\alpha}\left(\frac{\overline{Y}}{i^\alpha} - \overline{N}\right). \tag{3.9}$$

Using (2.3) and (2.4), the nonstochastic steady-state satisfies:

$$\begin{aligned} (\gamma_{\overline{Y}} + \delta - 1)\,\overline{Y} &= i^\alpha h, \\ (\gamma_N + \delta - 1)\,\overline{N} &= h. \end{aligned}$$

where $\gamma_{\overline{Y}} = \gamma_A^{\frac{\alpha}{1-\alpha}}\gamma_N$ denotes the gross rate of growth of $\overline{Y}$ and γ_N (resp. γ_A) is the gross growth rate of population (resp. TFP). Simple algebra now yields:

$$\left[\frac{\partial g}{\partial i}\right]_{steady\ state} = -\frac{1-\alpha}{\alpha}\frac{\gamma_N h\left(\gamma_A^{\frac{\alpha}{1-\alpha}} - 1\right)}{(\gamma_{\overline{Y}} + \delta - 1)\,(\gamma_N + \delta - 1)},$$

which is negative if and only if $\gamma_{\overline{Y}} > 1$ i.e. $\overline{Y}$ is growing.[5] Hence:

Result 2: In equilibrium, around the nonstochastic steady state, positive movements in the investment per new worker are linked to negative movements in the stock market value, if and only if the trend of TFP is non-negative.□

While this partial-equilibrium relationship between the stock market value and investment per new worker may seem mysterious at first, it is actually easy to understand by noting three properties of the model.

First, since we have heterogeneous capital goods, the aggregate response of the stock market to a TFP shock will be an average of the responses of each capital good. Hence the response is shaped by the cross-sectional distribution of machines' capital intensity.

Second, this cross-sectional distribution itself depends on the trend growth rates, which is why they appear in Result 2. TFP growth implies that this distribution shifts to the right over time

[5] Under the maintained assumptions that $\gamma_N \geq 1-\delta$ and $\gamma_{\overline{Y}} \geq 1-\delta$.

because of capital deepening: newer units are more capital-intensive (and thus more productive) than older ones. Hence, low productivity machines dominate the capital stock.

Third, if investors building new machines today choose a low capital intensity i_t for them, it must be that, given today's information (i.e. expectations of future wages, TFP and discount rates), low capital intensity machines are more profitable. Hence the value of low capital intensity machines rises when i_t falls. The only margin of adjustment in this economy adjust is the investment in new machines. Hence, the choices made by investors building new machines reveal the values through i_t. Of course i_t is an endogenous variable: the reason why it falls is ultimately that "shocks" hit the economy, and lead to low wages relative to productivity, making it optimal to invest in less capital-intensive units (i.e. higher cost or lower productivity units).

To summarize, if there is trend growth, low capital-intensity (and low productivity) machines dominate the cross-sectional distribution; and if i_t falls, low capital intensity machines gain relative to high capital intensity machines. Hence the aggregate stock market goes up if i_t falls. To get a sense for the magnitude of the effect involved, one can compute the impact response of the stock market to a shock that increases the capital intensity of new machines i by 1%:

$$\begin{aligned}\frac{\partial \log V}{\partial \log i} &= \frac{i}{V}\frac{\partial g(i,\overline{Y},\overline{N})}{\partial i}, \\ &\simeq -\frac{g_A}{n+\delta-g_A}.\end{aligned}$$

where g_A is the TFP growth rate. The parameters n, δ and g_A all together determine the shape of the cross-sectional distribution of machines. A higher n or δ implies that old, low capital-intensity machines make up a smaller share of existing capital, and the effect is thus smaller. Plugging in reasonable parameter values (e.g. $n = 1\%$, $g_A = 1\%$, $\delta = 6\%$) one obtains an elasticity of about -0.17. It follows that the large procyclical variations in stock values need to be explained by large countercyclical variations in investment per new worker i_t, since the elasticity is not large.

C. The impact of a TFP shock

The preceding analysis has explained the link between i_t and V_t but has taken as given movements in i_t. In a full general equilibrium model, shocks to TFP drive changes in i_t, and it is interesting to examine how this economy responds to such a shock.[6] The reaction of the stock market to a TFP shock is given by

$$\frac{\partial V_t}{\partial A_t} = \frac{\partial g}{\partial i}\frac{\partial i_t}{\partial A_t}.$$

[6] Other shocks could matter too, especially shocks to labor supply which will affect the cost of labor.

Since $\partial g/\partial i < 0$ assuming trend growth, we need $\partial i_t/\partial A_t < 0$ to generate a procyclical stock market. This means that an increase in TFP leads agents to anticipate a relatively low wage in the future as compared to interest rates, hence these agents will choose to invest in low capital-intensity machines, since labor will be relatively cheap.[7]

Moreover, as $I_t = i_t h_t$, if $\partial i/\partial A < 0$ we see that an expansion following a positive TFP shock will occur with h increasing markedly and i falling. That is, the economy responds to a shock by expanding capacity (the number of new machines), while lowering the average capital-intensity of each new machine. In Section 4, I provide some evidence that this pattern holds in the data.

I also find the case $\partial i/\partial A < 0$ realistic for the empirical reason that wages are rather smooth. Hence, a low capital-intensity or low productivity (low cost) unit is more attractive in booms. This can be seen directly from the cash flows $\pi_t(i) = A_t i^\alpha - w_t$: the proportional increase in cash flows $\Delta \log \pi_t/\Delta \log A_t$ is larger for low i machines if and only if $\Delta \log A_t > \Delta \log w_t$.

This "Schumpeterian" idea that old, low productivity firms are more procyclical is also featured in the theoretical study of Caballero and Hammour (1994). Their emphasis is on entry and exit, while I concentrate on factor cost differences. Bresnahan and Raff (1991) present interesting evidence from the Depression era, when aggregate investment was low and was geared towards new and more modern plants. Danthine and Donaldson (2002) also emphasize the role of wage smoothness; however, they rely on adjustment costs to create volatility in the cost of new capital. Finally, while the mechanism is different, this is related to the work of Greenwood and Jovanovic (1999), Greenwood and Yorukoglu (1997), Hobijn and Jovanovic (2001) and Laitner and Stolyarov (2003), who show that the introduction of new technology can sometimes reduce the value of existing capital.

D. Cross-sectional implications

The mechanism that I offer to generate variation in the value of the stock market has a natural cross-sectional implication: firms with high capital intensity should be less responsive (in profits or price) to an aggregate productivity shock. The proof is simple: given the formulas (3.6-3.7), 1% increase in TFP will decrease $q_{A,t}$ less than $q_{w,t}$, assuming $\partial i/\partial A < 0$. Thus, the value of a machine with capital intensity i, which is $P_t(i) = q_{A,t} i^\alpha - q_{w,t}$,will go up by less if i is larger. This is because the present value of labor costs $q_{w,t}$ increases by less than the present value of sales

[7]In the DSGE extension of this model, with TFP shocks and a representative agent, I found in numerical simulations that to obtain the condition $\partial i/\partial A < 0$, it is necessary to have a very elastic labor supply (so that the cost of labor is not very cyclical) and a low intertemporal elasticity of substitution of consumption.

$q_{A,t}$; this again is ultimately (in general equilibrium) due to the smoothness of wages. In [author name], I develop these implications of the model and I find some empirical support for them. Firms with low average q (or high book-to-market) have highly procyclical profits, and they also have high expected returns.

4 The empirical link between stock returns, investment, and job creation

In this section, I evaluate the empirical relevance of the putty-clay model in explaining stock returns. To do so, I use the production-based asset-pricing formula $V_t = g(i_t, \overline{Y}_t, \overline{N}_t)$, which I derived in the previous section. This formula can be used to map macroeconomic time series directly into stock returns, without reference to consumption. This is very similar to what is typically done with the adjustment cost model. I compute the share of return volatility due to the putty-clay component and the share due to the adjustment cost component, and I find that they are similar: each feature accounts for about 50% of return volatility. Before turning to returns, I first measure and quantify the behavior of the key variable introduced by the putty-clay model: investment per new job.

A. The volatility and countercyclicality of investment per new job

The return predicted by the putty-clay model is volatile and procyclical only if i_t is volatile and countercyclical (this is the condition $\partial i/\partial A < 0$ studied in Section 3). In this Section, I construct an empirical counterpart for i_t and I examine the behavior of this series. In the model the variable i_t is aggregate investment I_t divided by the number of new jobs h_t. Hence, to obtain i_t I simply compute gross job creation $h_t = \overline{N}_{t+1} - (1-\delta)\overline{N}_t$ given data on employment $\overline{N}_t$, and then divide aggregate non-residential investment I_t by h_t. This process requires to choose a value for δ. In the model, capital depreciation and job destruction are equal; in the data they are not, which makes the choice of δ more complicated. Capital depreciates at a rate of about 6% per year, while gross job destruction is about 10% per year.[8] The results I present are based on a compromise value of 8%. The exact results do depend on this choice, but any depreciation rate between 6% and 10% generates similar results (more on this later).

Figure 1 displays the time series of $\log h_t$ and $\log i_t$. Gross job creation $\log h_t$ trends up due to population growth, but the volatility is substantial. The investment per new job $\log i_t$ also trends up, as the capital intensity increases over time in the U.S. economy, but it also exhibits

[8] This number is from Table 1 of Foster, Haltiwanger and Kim (2006).

large countercyclical fluctuations. Even though investment is procyclical, $\log i_t$ is countercyclical because job creation is highly procyclical. This suggests that the model has the potential to generate stock market volatility.

The business cycle properties of the variables h_t and i_t are shown in Table 1 along with investment, GDP, and the aggregate stock return. Gross job creation h_t is procyclical and very volatile, about three times as much as investment. Investment per new job i_t is also very volatile. These statistics suggest that the condition $\partial i/\partial A < 0$ is realistic: in good times, aggregate investment I_t goes up through an expansion of capacity (jobs) h_t, but the average investment per new job i_t actually falls (see the discussion in Section 3C). In the data, the correlation between the cyclical components of i_t and stock market value is -0.26, so that the basic negative correlation of V and i is indeed true.

B. Stock Returns: Putty-Clay vs. Adjustment Cost

To evaluate the ability of the putty-clay model to explain empirically asset values, I construct the investment return implied by the model, and compare it with the data. This is similar to the test Cochrane (1991) performed for the adjustment cost model. In the analysis of Sections 2 and 3, I made several assumptions which make the model's implications starker and easier to analyze. To bring the model to the data, I prefer to be less restrictive; hence I first augment the model with a standard adjustment cost.[9] Next I evaluate the relative importance of the adjustment cost component and the putty-clay component in explaining stock returns.

Assume, then, that when the representative firm builds new machines, it has to buy capital at price Q_t. This price reflects the rising supply curve (external adjustment cost) of a capital-good producing sector. Using the standard formulation yields $Q_t = 1 + \phi\left(\frac{I_t}{K_t}\right)$ where ϕ is the marginal cost of adjustment. The firm's program is then a simple variation on the program studied in Sections 2 and 3:

$$\max_{i_t \geq 0} \left\{ P_t(i_t) - Q_t i_t \right\},$$

and the free entry condition reads: $P_t(i_t) = Q_t i_t$. The same steps as in Section 3 yield a modified

[9] It would be interesting to also relax the assumption of full utilization for the empirical work. However this would require a very different approach, because the formula (3.9) that I use cannot be easily generalized to the case of variable utilization. In the appendix I show in numerical simulations of the DSGE model that prices are similar in the model with variable utilization, and that the values of firms with low capital intensity are actually even more procyclical because of the option value of closing.

version of (3.8):

$$V_t = Q_t \times g(i_t, \overline{Y}_t, \overline{N}_t). \tag{4.1}$$

This formula naturally mixes the adjustment cost model (through the marginal Q term) and the putty-clay model (through the function g).

Construction of the Investment Return

The return implied by this value formula is:

$$R_{t+1} = \frac{V_{t+1} + D_{t+1}}{V_t + I_t}, \tag{4.2}$$

where D_t is the payout to capital owners (output minus labor payments) and I_t is total investment. The unusual denominator term I_t needs to be introduced because our formula for the value at date $t+1$ takes into account the existing stock of capital at the beginning of time $t+1$, and this capital is obtained by buying the capital that exists at the beginning of date t at price V_t, plus the new investment projects at their cost I_t. The terms D_{t+1} and I_t turn out to be relatively unimportant since they are smooth compared to the stock market value.

To construct $g(i_t, \overline{Y}_t, \overline{N}_t)$, I use the equation (3.8),

$$g(i_t, \overline{Y}_t, \overline{N}_t) = \frac{i_t}{\alpha}\left(\frac{\overline{Y}_t}{i_t^\alpha} - (1-\alpha)\overline{N}_t\right).$$

The construction of i_t has been discussed above: given $\delta = 0.08$, it is simply $I_t / \left(\overline{N}_{t+1} - (1-\delta)\overline{N}_t\right)$, where $\overline{N}_t$ is total employment. To obtain $\overline{Y}_t$, I simply iterate on the model's second state law of motion:

$$\overline{Y}_{t+1} = (1-\delta)\overline{Y}_t + i_t^\alpha h_t,$$

using the series constructed above for i_t and h_t. To do this, I need to assume a value for α and $\overline{Y}_0$ (δ is still 0.08). Since α is the long-run average capital share, I set $\alpha = 0.3$; this parameter has little impact on the results. $\overline{Y}_0$ is assumed to be at the steady-state value; obviously, the impact of this initial condition disappears after a few periods, hence this setting is also not very important. I take D_{t+1} and I_t directly from the data.[10]

[10] The data used in this section are as follows. Aggregate investment is real non-residential investment from the BEA. For the putty-clay model, the employment series is the establishment survey series (total employees on private payrolls, [PAYEMS] on the FRED website). Similar results are obtained when the series is instead either the household survey on employment (civilian employment over age 16 [CE16OV]) or a BLS index of total hours worked [HOABNS]. For the adjustment cost model, the capital series is the non-residential capital stock from the fixed asset tables. The "dividend" is computed as net interest plus corporate profits (lines 15 plus 18) from the table 1.12 of the National Income and Product Accounts. The stock market return is from CRSP. The sample is

Finally, to construct marginal Q, I assume a standard quadratic adjustment cost, leading to:

$$Q_t = 1 + \kappa \left(\frac{I_t}{K_t} - \delta \right),$$

where κ is the adjustment cost parameter. This means that adjustment costs are paid when net investment is positive.[11] I use two values for κ: $\kappa = 2$ which is on the high side of typical microeconomic estimates,[12] and $\kappa = 14.41$, which is the value which maximizes the fit of the adjustment cost model (as measured by the pseudo-R^2 below). This parameter implies large adjustment costs as noted at least since Summers (1980).

I also compute the investment return implied by the "pure" putty-clay model (i.e., without adjustment costs) by setting $Q_t = 1$ in the formula (4.1), as well as the investment return implied by the "pure" adjustment cost model using the standard Hayashi (1982) formula $V_t = q_t K_t$ in (4.2).

Empirical Results

Table 2 presents some measures of fit for the different models; I consider models with only putty-clay technology, with only adjustment cost technology, or with both. I present results for different adjustment cost parameters. This table gives the volatility of each return, the correlation with the data return, and a measure of fit (pseudo-R^2):

$$\mathbf{R}^2 \overset{def}{=} 1 - \frac{\frac{1}{T}\sum_{t=1}^{T}\left(R_t^{\text{model}} - R_t^{\text{data}}\right)^2}{Var(R_t^{\text{data}})},$$

which lies between 0 and 1 only if the model fits the data better than a constant.

Table 2 reveals that the pure putty-clay technology generates a return volatility of about 10% per year. For low values of κ, the adjustment cost model does not fit the data well. For high values of κ, it does roughly as well as the putty-clay model. (The fit improves hardly when even higher values of κ are considered.) This table also shows that there is a clear improvement of fit when the adjustment cost model is superimposed on the putty-clay feature. The pseudo-R^2 increases noticeably, and so does the correlation between the model return and the data return. Finally, the volatility of the return is consistently higher when both features are present. Figure

1950 to 2004. Note that since computation of the stock value for the putty-clay model requires knowledge of i_t and thus of $\overline{N}_{t+1}$ I can infer values only up to the start of 2003 and so my last return is the one during the year 2002. Following the usual convention, I attribute the value to the beginning of the period.

[11] The results are very similar when adjustment costs are paid when gross investment is positive, i.e. $Q_t = 1 + \kappa I_t / K_t$ (as in a previous draft).

[12] For instance, Gilchrist and Himmelberg (1995) and Cooper and Haltiwanger (2006) both estimate that κ is around 1.

2 presents the return implied by the model with both the putty-clay and the adjustment cost features (for $\kappa = 14.41$) along with the data and the returns implied by the "pure" putty-clay model and the "pure" adjustment cost model. Interestingly, the models appear to complement each other to increase the fit.[13]

Decomposing the return variability into adjustment cost model and putty-clay model

I now ask: how much of the return volatility is due to the putty-clay feature and how much is due to the adjustment cost feature? In the model where both features are present, a natural decomposition arises between the variation in Tobin's Q and the putty-clay element $g(i_t, \overline{Y}_t, \overline{N}_t)$. More precisely, the following approximation to the return is fairly accurate:

$$\begin{aligned} R_{t+1} &\simeq \frac{V_{t+1}}{V_t} \simeq \frac{Q_{t+1} \times g(i_{t+1}, \overline{Y}_{t+1}, \overline{N}_{t+1})}{Q_t \times g(i_t, \overline{Y}_t, \overline{N}_t)} \\ R_{t+1} - 1 &\simeq \underbrace{\frac{Q_{t+1}}{Q_t} - 1}_{\overset{def}{=} R^{ac}_{t+1}} + \underbrace{\frac{g(i_{t+1}, \overline{Y}_{t+1}, \overline{N}_{t+1})}{g(i_t, \overline{Y}_t, \overline{N}_t)} - 1}_{\overset{def}{=} R^{pc}_{t+1}}, \end{aligned}$$

hence I define the share of return volatility due to the putty-clay feature as

$$\omega = \frac{Cov(R^{pc}_{t+1}, R_{t+1})}{Var(R_{t+1})}.$$

An alternative measure can be proposed. Assume that a share θ of the economy behaves as in the putty-clay model and the remaining share $1 - \theta$ as in the adjustment cost model. The total stock return is a weighted average of the two models. I can then find the share θ which maximizes the fit with the data. Formally, define $R_t(\theta)$ as:

$$R_t(\theta) = \theta R^{pc}_t + (1 - \theta) R^{ac}_t,$$

and choose θ as a nonlinear least square estimator:

$$\theta \in \arg\min \frac{1}{T} \sum_{t=1}^{T} \left(R_t(\theta) - R_t\right)^2.$$

The results from these two procedures are presented in the last two columns of Table 2. Remarkably, these two measures yield very similar answers. For high adjustment costs, around 50-60%

[13] The volatility of implied gross job creation h_t depends on the value of δ. When δ is low, the variable becomes more volatile, and hence i_t becomes more volatile as well. As a result, the stock return predicted by the model becomes more volatile. For instance, if $\delta = 0.07$, the share of return volatility due to the putty-clay component rises from 62.8% to 81.9%. On the other hand, if $\delta = 0.09$, the share of return volatility falls to 45.7%. The correlation between model return and data return is 0.57 for $\delta = 0.07$, 0.56 for $\delta = 0.08$ and 0.51 for $\delta = 0.09$.

of total return variability is attributable to the putty-clay feature. It thus appears to be roughly as important as the adjustment cost feature.

The lead-lag relation between GDP growth and the stock return

An interesting aspect of the dynamics of the stock market return is that it predicts output growth (e.g. Fisher and Merton (1984), Stock and Watson (2003)). To see whether the putty-clay or adjustment cost model is able to reproduce this result, I run a simple regression of GDP growth on either the current or lagged stock market return for each model and for the data.[14] Table 3 shows that in the data, stock returns are not correlated with current GDP growth, but they predict GDP growth one year ahead significantly. The putty-clay model appears to be better at capturing the patterns of signs and R^2 of these regressions than the adjustment cost model. This is an interesting fact because it reflects one well-known defect of the adjustment cost model: its return lags the empirical return (Lamont (2001)). The intuition for this empirical result is straightforward. In the data, the stock market moves before GDP, while the stock return of the adjustment cost model moves contemporaneously with investment (by construction), and investment is roughly coincidental with GDP. The putty-clay model works better because the stock value increases when job creation is high relative to investment - a pattern which is typical in the early stages of recoveries in the data.[15]

The stock market boom of the 1990s

The conclusion of this empirical section is that the putty-clay technology generates a volatile stock market return, which helps to improve on the adjustment cost model. Interestingly, Figure 2 suggests that the putty-clay model fits worse since 1990 than in the preceding decades, while the adjustment cost model fits well in the 1990s. I did not find any clear-cut explanation why. Mechanically, this is because of the very robust investment growth of the late 1990s, which implies a smoothly increasing investment per worker i_t. If the price of capital goods is underestimated, then the model would be closer to the data. Another possibility is that due to some change in parameter, the model's formula does not fit well the data anymore. A parameter that may be shifting is δ, the rate of depreciation, since IT-related investment goods represents a growing share of the capital stock. According to the formula on p.11 the putty-clay model generates less

[14] I obtained very similar results adding lagged GDP growth as a right-hand side variable; or with a VAR with both short-run orthogonalizations; or using quarterly data.

[15] Job creation is volatile and procyclical even when total employment lags output (the flow is volatile even if the stock is not). The pattern is less strong in the last two ("jobless") recoveries - as we can see in Figure 2, the putty-clay model does not match very well the last two recessions.

variation in price for a given change in i when δ is higher, because with a high δ, the cross-sectional distribution is less geared towards old capital goods. However, the improvement in fit when I change the δ value for the 1990s is slight. This deserves further study.

5 Concluding remarks

Ever since Hansen and Singleton (1982), much work has been devoted to evaluate whether stock returns fit consumption data and preferences. But in general equilibrium, stock returns should also fit investment and the production side of the economy. This paper shows that the putty-clay model makes some progress toward reconciling the production side of the economy with stock returns. This work complements Gilchrist and Williams (2000) who found that the putty-clay technology also delivers interesting business cycle implications. Many of these business cycle implications are maintained in the simple variant I develop and which may prove useful for other applications.

More generally, my empirical results show that job creation is empirically relevant to explain stock market movements. These results are thus supportive of models that link labor movements to firm valuation; labor is a more important input than capital in most industries, and one reason why firms earn quasi-rents is that assembling a team of workers takes time and is costly (e.g., Merz and Yashiv (2006)). It seems fruitful to study further these microfoundations for the valuation of capital.

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	h_t	i_t	$I_t = i_t h_t$	y_t	R_t
Standard Deviation	0.191	0.162	0.068	0.021	0.177
Correlations	h_t	i_t	I_t	y_t	R_t
h_t	1				
i_t	-0.94	1			
$I_t = i_t h_t$	0.58	-0.28	1		
y_t	0.72	-0.55	0.74	1	
R_t	-0.36	0.34	-0.21	-0.29	1

Table 1: Business cycle statistics for i(t)=investment over gross job creation, h(t)=gross job creation, I(t) = nonresidential investment, y(t) = real GDP, and R(t) = stock return. Annual Data. All variables except the stock return are logged and HP filtered with lambda=100.

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	$\sigma(R)$	Corr(Rmodel,Rdata)	$\mathbf{R}^2$ (%)	Share ω	Share θ
Data	17.70	—	—	—	—
Putty-Clay (PC)	10.29	0.56	27.85	—	—
Net Adjustment Cost (AC), $\kappa = 2$	2.14	0.37	0.76	—	95.5
Net Adjustment Cost (AC), $\kappa = 14.41$	7.76	0.52	20.20	—	62.8
PC+Net AC, $\kappa = 2$	10.84	0.59	31.77	94.4	—
PC+Net AC, $\kappa = 14.41$	14.79	0.65	36.89	62.5	—

Table 2: Measures of fit for the different models. PC=putty-clay model, AC=adjustment cost model, PC+AC=model with both putty-clay and adjustment cost. The table indicates for each model the volatility of the investment return implied by the model, the correlation between the investment return and the data return, the pseudo-R2, and a measure (omega or theta) of the share of return volatility due to the putty-clay feature (defined in the mai text).

	Current return				Lagged return			
	β	$\sigma(\beta)$	R^2	$\rho_{R,GDP}$	β	$\sigma(\beta)$	R^2	$\rho_{R_{-1},GDP}$
Data	-0.008	0.017	0.00	-0.06	0.088	0.011	0.43	0.66
Putty-Clay (PC)	-0.081	0.018	0.12	-0.34	0.156	0.015	0.48	0.69
Net Adjustment Cost (AC), $\kappa = 2$	0.241	0.169	0.05	0.21	0.667	0.119	0.39	0.63
Net Adjustment Cost (AC), $\kappa = 14.41$	0.093	0.035	0.09	0.30	0.223	0.017	0.57	0.76
PC+Net AC, $\kappa = 2$	-0.066	0.019	0.09	-0.30	0.158	0.016	0.55	0.74
PC+Net AC, $\kappa = 14.41$	-0.017	0.020	0.01	-0.10	0.130	0.013	0.71	0.85

Table 3: Regressions of GDP growth on the current or lagged return, for each model and for the data. The table gives the coefficient on the return, the standard error computed with the Newey-West formula with three lags, the adjusted R2, and the correlation between GDP growth and the current return.

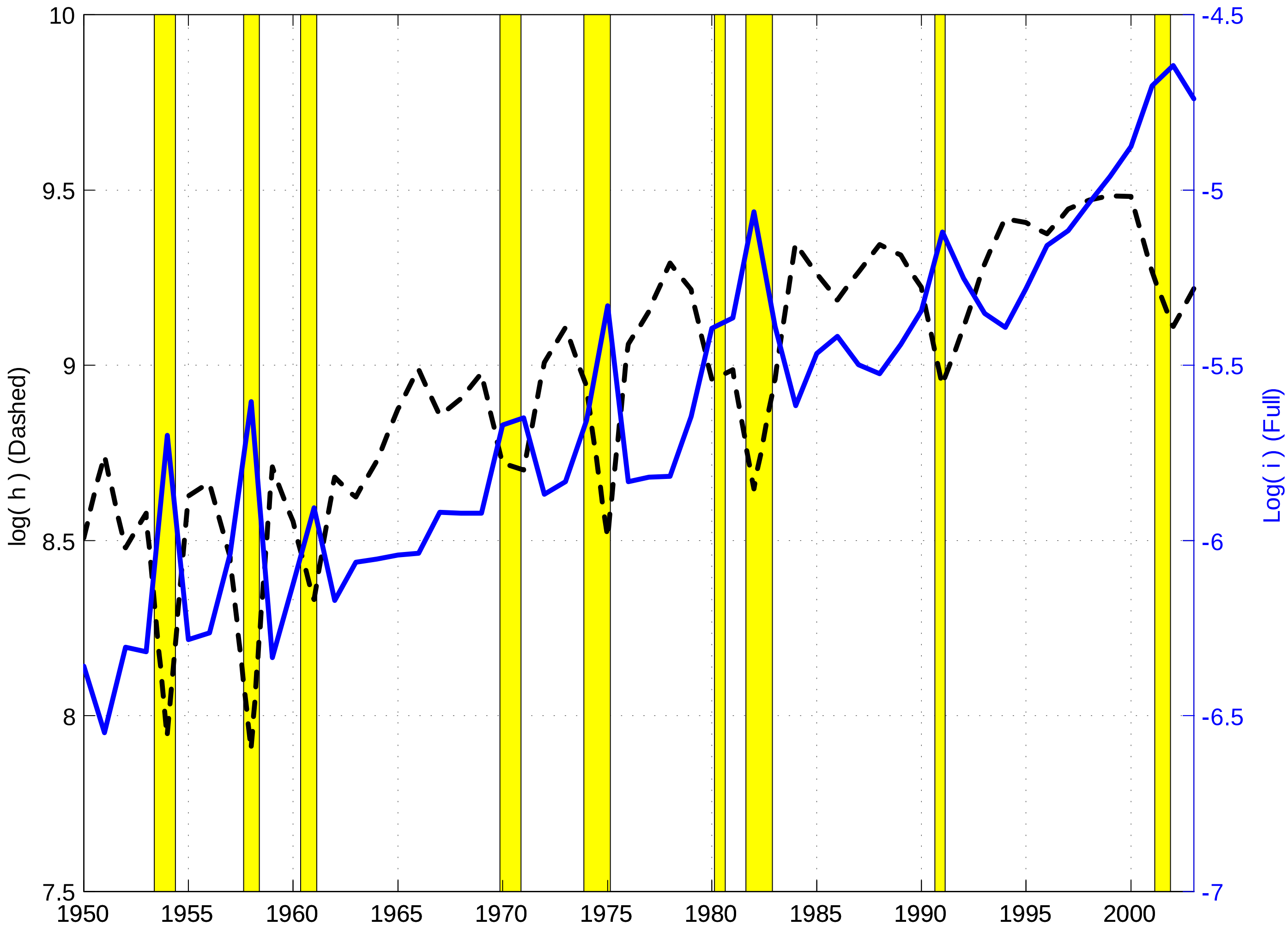
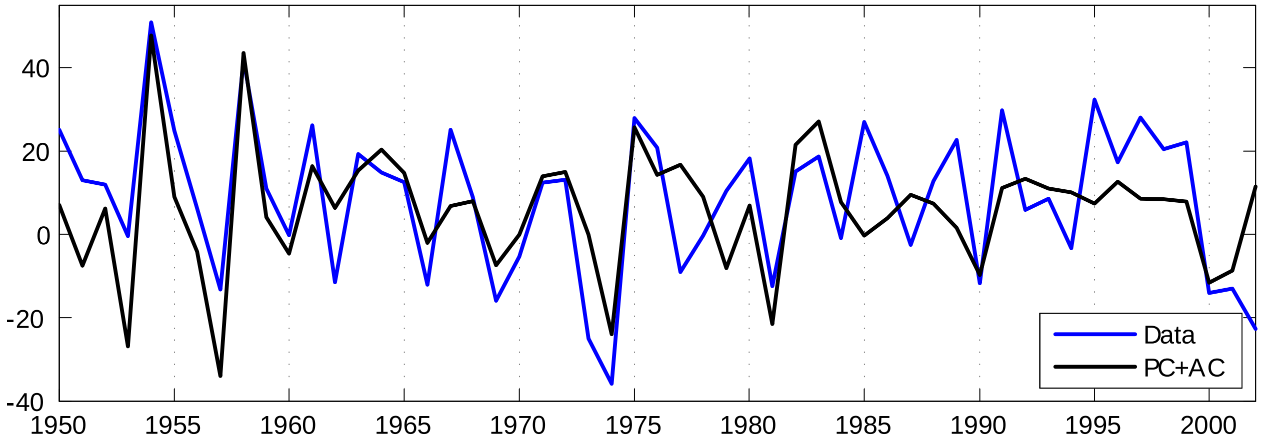


Figure 1: Log gross job creation $h(t)$ (dashed line, left scale) and log investment per new job $i(t)$ (full line, right scale). Gross job creation is obtained by quasi-differencing total employment from the Current Employment Survey ($\delta = 0.08$). Investment per new job is constructed as the ratio of non-residential investment (BEA) over gross job creation. Annual data. NBER recessions are indicated as shaded areas.



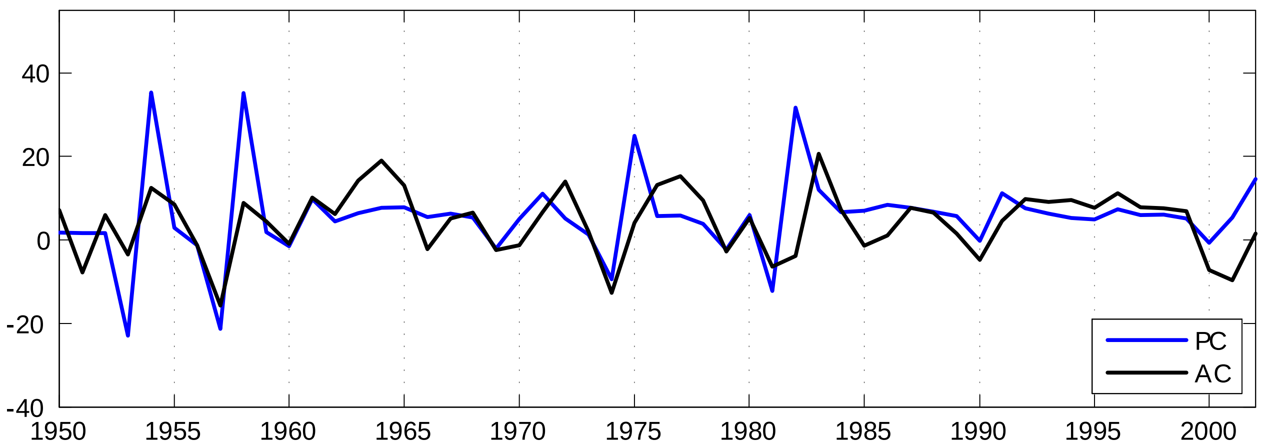


Figure 2: The top panel plots the stock return from the data (light line) and from the model with bpth putty-clay technology and adjustment costs (dark line). The bottom panel plots the stock return from the pure putty-clay model (light line), and from the pure adjustment cost model (dark line).