Essays on Asset Pricing

by

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To Abbigail and Freya.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table

ABSTRACT

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My dissertation aims to explain two features of Asset Pricing: the "high tech bubble" and the return comovement anomaly.

In Chapter One, I show that a generalized version of the standard neoclassical investment model can explain the relatively high equity prices in the late 1990s and early 2000s in the US corporate nonfinancial and NASDAQ sectors along with the relatively low prices before and after this period. Stock returns predicted by the model are as volatile as the observed stock returns in both sectors. Three key model assumptions are multiple capital goods, investment-specific technological change and non-quadratic adjustment costs. During the "bubble" period, investment in equipment is relatively high — consistent with high expected cash flows and high prices. Investment rates subsequently fall — consistent with lower expected cash flows and lower prices. On average, managers' forecasts are correct. Increases in the growth rate of equipment investment coincide with decreases in measured productivity growth. This is consistent with the unobserved diversion of labor from producing output towards accumulating human capital or other intangible assets.

In Chapter Two, I examine the role of information in explaining excess comovement in asset returns. Many studies have documented stock return comovement above and beyond that predicted by standard asset pricing models. Furthermore, when stocks are added to an index, their betas with respect to that index tend to increase. I find that much of this excess comovement can be explained by correlated information. If individual analysts earnings forecast errors are correlated across stocks, the stock return correlations should be higher than fundamental correlations. I develop a measure of correlated analyst coverage to test this hypothesis and find: (1) Stocks with similar analysts tend to exhibit more excess comovement, (2) On average, when a stock enters the S&P 500 index, the same analysts that cover other S&P 500 stocks begin to cover the new stock, and (3) Changes in excess comovement are larger for stocks with larger increases in correlated analyst coverage around this event. This measure does not seem to be proxying for correlations in risk or unexpected earnings.

CHAPTER I

Investment Based Valuation

1.1 Introduction

The neoclassical investment model with capital adjustment costs is a workhorse in the investment literature and has been used to explain many perceived anomalies in the cross section of stock returns. However, the model in its standard form is unable to explain the magnitudes of the significant run-up and subsequent fall in market values of equity during the late 1990s and early 2000s. This leaves two possibilities: either 1) the neoclassical framework cannot account for observed stock price behavior during this period and we need to appeal instead to investor irrationality (e.g., Hong and Stein, 1999) or time-varying uncertainty (e.g., Pastor and Veronesi, 2003, 2006); or 2) the standard neoclassical model needs to be patched up so that it can account for observed stock price behavior during this period. This paper shows that three modifications to the assumptions of the standard model, all of which are consistent with the spirit of the neoclassical framework, allow the model to accommodate the large changes in equity values observed during the late 1990s and early 2000s along with the high stock return volatility.

In the model's standard form (à la Cochrane, 1991), firms maximize shareholder value by choosing levels of investment in productive fixed capital which is subject to quadratic adjustment costs. In this framework, the equilibrium market value of the firm's equity, p_t, plus its debt, b_t, is equal to its capital stock, k_{t+1}, times the shadow price of capital, q_t, or marginal q:

$$p_t + b_t = q_t k_{t+1}.$$

Figure 1.1 shows the actual market values of equity scaled by output for the US corporate nonfinancial sector from 1953 to 2005 and the NASDAQ sector from 1983 to 2005 along with the fitted values predicted by the standard model using a Generalized Method of Moments estimation procedure. The model is able to fit mean levels, but is not flexible enough to explain the extreme changes in prices — especially during the "bubble" period.

I modify the standard model in three ways. First, I make a distinction between structures capital (real estate, buildings, etc.) and equipment capital (machines, software, etc.). In practice, fixed capital is heterogeneous both in terms of productivity *and* in terms of capital adjustment costs. For example, a square foot of office space is not necessarily a good substitute for a new software package of the same value in terms of producing goods and services. Also, more time is likely to be diverted towards learning how to use the software package than towards learning to navigate a new room. In equilibrium, marginal q is equal to both the discounted marginal cash flows from investment *and* the marginal capital adjustment costs. If firms simply scale all inputs up and down over time in fixed proportions, the standard model may suffice, despite the heterogeneity. However, the composition of the aggregate capital stock has shifted from structures towards equipment in both sectors recently, but not necessarily monotonically. Additionally, equipment investment-capital ratios tend to be more pro-cyclical than corresponding structures ratios. This assumption is crucial in both the US corporate nonfinancial and NASDAQ sectors.

Second, I adjust for the changing quality of equipment capital. Standard models hold the productive quality of capital constant. In reality, the quality of new capital – especially equipment – changes over time. A common example used to illustrate this "investment-specific technological change" is "Moore's Law" which states that the number of transistors that can be inexpensively placed on an integrated chip doubles approximately every two years. If the price of the chips increases at a lower rate than the productivity, then the real price of a chip will underestimate the level of technology embodied in each new vintage of hardware. This assumption is especially important in the NASDAQ sector which is more heavily invested in equipment capital.

Third, I allow adjustment costs to be non-quadratic. Quadratic adjustment costs are primarily used for analytic convenience: with such adjustment costs, q_t is linear in investment-capital ratios. However, there is no ex-ante reason to expect a quadratic function to provide a better approximation of adjustment costs than another convex function. Because this function determines changes in q, its curvature is important in determining the price levels, price changes, and the volatility of price changes. The power of the adjustment cost function is a measure of the elasticity of q_t with respect to changes in investment. Holding the marginal cost level fixed, increases in the curvature of the cost function decrease total adjustment costs – which can be used to test the plausibility of the model. Allowing for non-quadratic costs permits the model to generate relatively high prices and relatively low total adjustment costs.

When the standard neoclassical investment model is extended to include heterogeneous capital, investment-specific technological change and non-quadratic adjustment costs, it can explain most of the extreme price movements during the "bubble" period in both sectors. The equilibrium pricing equation from this generalized model is

$$p_t + b_t = q_t^s s_{t+1} + q_t^e e_{t+1},$$

where s_t and e_t are the structures and quality-adjusted equipment capital stocks, respectively, and q_t^s and q_t^e are the corresponding shadow prices. Figure 1.2 shows the actual market values of equity scaled by output for each sector along with the values predicted by the generalized model. The model performs very well during the “bubble”. During this period, investment is high. This is consistent with managers willing to incur relatively high adjustment costs because they expect high marginal cash flows from investing. When expected cash flows are high, prices are high. Managers subsequently decrease rates of investment, expecting marginal cash flows to be lower in the future. Low marginal cash flows mean low prices. On average, their forecasts are correct. The time series of prices reflects the time series of investment.

During the “bubble” period, adjustment costs associated with equipment investment are relatively high. Investment in new equipment must be accompanied by possibly unobservable complementary investment in human capital or intangible capital. This is consistent with the nature of investment in technologically advanced equipment observed during this period. Furthermore, controlling for price, each new vintage of equipment capital is more productive than the previous. As firms replace old capital with newer, more productive capital, this leads to an additional increase in value. When investment is high, this is especially pronounced. Indirect adjustment costs for structures investment are close to zero.

I also examine the effect of heterogeneous capital, investment-specific technological change, non-quadratic adjustment costs and leverage on the empirical relation between investment and stock returns and I compare the results to Cochrane’s (1991) results in terms of volatilities and autocorrelations of returns. In particular, I generate the model predicted stock returns and find them to be as volatile as observed returns. Cochrane (1991) uses a model with homogeneous capital, quadratic adjustment costs and all-equity financing and generates a stock return standard deviation of less than half of the actual value. The model in this paper generates quarterly return standard deviations of about 6.1% in the US corporate nonfinancial sector and 12.6% in the

NASDAQ sector compared to the observed standard deviations of 6.4% and 10.4%, respectively. The adjustment costs associated with structures are essentially zero. Most of the results are driven by equipment capital. In the US corporate nonfinancial sector, heterogeneous capital and debt financing have the biggest effect on stock return volatility, but non-quadratic adjustment costs are also important. Generating high stock return volatility is much easier on the NASDAQ, where investment-capital ratios are much more volatile.

Both firm value and stock returns are functions of investment. When adjustment costs functions are quadratic, marginal returns from investing are linear in the investment-capital ratios. When the powers are greater than two, the relation between marginal returns and investment is convex. From a shareholder's perspective, if investment is unexpectedly high next quarter, the marginal cost of investment will be higher than in the quadratic case. Controlling for the other parameters, the volatility of the investment-capital series is amplified relative to the quadratic adjustment costs case. As a result, stock returns are more volatile.

Adjustment costs are crucial to the model. Managers increase investment up to the point at which the marginal cost of investment – including adjustment costs – is equal to the marginal expected profit from investment. If *marginal* costs are too low, the implied marginal profits, and equity value will be too low. On the other hand, if *total* adjustment costs are too high, the model may be inconsistent with reality. Allowing the curvature of the adjustment costs function to depart from the quadratic case generates relatively high equity prices and relatively low total adjustment costs. The implied adjustment costs from the model are reasonably small for the US corporate nonfinancial sector – 2% of output per quarter – and slightly larger for the NASDAQ – about 12% of output. Average marginal adjustment costs are 1 for structures and 1.954 for equipment compared to 1 and 7.331 in the NASDAQ. These all lie within the range of previous estimates[1].

I find that measured productivity growth drops with increases in equipment investment growth, consistent with accumulation of human capital during periods of high investment. If equipment capital and human capital are complementary inputs in the production function, periods of high investment in equipment will coincide with periods of high investment in human capital. Human capital is accumulated through the process of learning. When new equipment is introduced, workers must spend time learning the best way to use it. This diversion of labor from producing output towards learning how to use new capital reduces output. Because labor is not disaggregated into time spent learning and time spent producing, measured productivity is low when investment in equipment is high. I do not find a statistically significant effect for structures investment. This is consistent with small indirect structures adjustment costs.

I cannot rule out every behavioral explanation for the "bubble", nor do I attempt to do so. Instead, I provide a rational model that is consistent with the prices, returns, and return volatilities observed during this period. I also do not directly model expectations. I cannot explain why investment is high during the late '90s. However, I do show that it is consistent with rational decision making on the part of the firm. On average, firms' forecasts about returns from investing are correct - both unconditionally and controlling for predictive variables. Prices are high because investment is high, and on average, high investment is followed by high returns from investing.

High investment alone does not lead to high firm value. Both the level of investment and value of the firm are determined in equilibrium as a function of unobserved expected productivity of capital. If the expected marginal return from investing is

[1] Merz and Yashiv (2005) find capital adjustment costs that average 4.2% of output in the US corporate nonfinancial sector. To my knowledge no previous estimates of average adjustment costs on the NASDAQ exist. Past estimates of marginal adjustment costs range from about 1 (Cooper and Haltiwanger, 2006) to 10.5 (Cummins et al., 1994)

high, investment will be high, and so will firm value. Furthermore, if marginal adjustment costs are increased for the same equilibrium levels of investment, it must be that rational managers expect equally high marginal returns from investing. In such an equilibrium, firm value will be even higher. High investment, high marginal adjustment costs, and high firm value are consistent with high expected marginal returns from investing.

1.1.1 Related Literature

The methodology in this paper is related to that in Merz and Yashiv (2005, 2007) who examine the effect of labor market frictions and capital adjustment costs on the value of the firm. In such an economy, labor adds to the market value of the firm. They are able to explain much of the relative difference in levels from the 1970s through the late 1990s and early 2000s. Instead of focusing on labor or intangible assets, I show that by disaggregating fixed capital into two components, structures and equipment, accounting for changes in the quality of equipment, and incorporating non-quadratic adjustment costs, a neoclassical q-theory model can explain the high price levels in the late 1990s and early 2000s relative to other years in both the US corporate nonfinancial and NASDAQ sectors. Merz and Yashiv do not examine the high tech sector or the relation between investment returns and stock returns.

The valuation literature has two major strands. The first consists of papers using partial and general equilibrium neoclassical models to explain firm value. The benefit of using these models is that firm value is a function of potentially observable variables. If the firm is behaving optimally, the shadow price of capital, q_t, is an objective forecast of discounted marginal cash flows. The firm's optimal forecast is used in lieu of a subjective forecast. While q_t may not be directly observable, it is a function of a firm's observable investment decisions. Several papers add unmeasured intangible capital in the valuation context to explain firm value. Hall (2001) defines intangible capital as the difference in the market value of the firm and the value of the firm's tangible capital. By construction, the model fits the data perfectly. McGrattan and Prescott (2005, 2007) use first order conditions to infer intangible capital and investment and are able to generate a run-up in scaled US corporate values from the 1970s to the late 1990s. Because they use general equilibrium models, they rely on aggregate consumption data and wage data and do not examine individual firms or sectors.

At the other extreme are papers using accounting-based methods: relative valuation, in which a firm's financial ratios (e.g., price-to-earnings and market-to-book equity) are compared to peer firms, and discounted cash flow analysis, which involves discounting projected future cash flows at the appropriate risk-adjusted rate. Both types of valuation are widely used in practical applications. However, both types also involve an amount of subjectivity in the form of growth forecasts and discount rates.

Pastor and Veronesi (2003, 2006) use the clean surplus accounting relation to model dynamics of the book value of equity. To relate book value and market value, they assume that at some random time in the future the two will be equal. They parameterize the firm's productivity process and assume that investors know all of the model parameters with certainty except for the firm's average profitability. Through the process of learning, investors update their beliefs about this parameter. Because market values are convex in average profitability, firm valuations increase with investors' uncertainty about average profitability. After calibrating the model using annual data, they find the implied levels of uncertainty about average profitability for several NASDAQ stocks necessary to justify the prices at the height of the "bubble" and argue that they are reasonably small.

In the model in this paper, there is no uncertainty about model parameters on the part of investors. Instead, the investment decisions of managers are taken as given. Any learning about profitability is implicitly embedded in the observed investment decisions. Rational managers will equate marginal costs with marginal returns. Given the amount of fixed capital of the firm and the adjustment costs function, managers' investment decisions perfectly reveal their forecasts about profitability. The rational market value of the firm immediately follows. In order to ensure that observed investment decisions are consistent with rationality, I include the investment Euler equations as moments in the estimation procedure. On average, managers' one period ahead forecasts of profitability are correct – both unconditionally and with respect to the instruments. These two first order conditions restrict the set of parameter estimates to those that are consistent with rational decision making. Pastor and Veronesi (2003, 2006) do not directly use the information contained in a firm's investment decisions. Instead, they use a reduced form approach and model the profitability process itself. Using the investment information could shed further light on the plausibility of their parameter values and the implied uncertainty about average profitability.

Section 2 describes the model and its implications. Section 3 presents the empirical strategy. Section 4 describes the data construction and summary statistics. Section 5 presents the empirical results for the main model along with alternate specifications. Section 6 examines the effect of investment on productivity growth. I conclude in Section 7.

1.2 The Model

I use an augmented version of the standard neoclassical q-theory model. Firms use two capital inputs to produce homogeneous output. In the basic q-theory model, all types of fixed capital are treated equal. In practice, capital is heterogeneous in terms of productivity, adjustment costs and depreciation. In the production process, an expensive machine is not necessarily a good substitute for a small piece of real estate of the same value. To capture these differences, and to test the importance of these distinctions in valuation, I incorporate multiple capital goods into the model.

Output, $\pi(s_t, e_t, \theta_t)$, depends on the stocks of structures, s_t, and equipment, e_t, and a vector of exogenous aggregate, firm- and input-specific productivity shocks, θ_t. To simplify the notation, I suppress these arguments and define $\pi(t) \equiv \pi(s_t, e_t, \theta_t)$. The production function exhibits constant returns to scale, so that $\pi(s_t, e_t, \theta_t) = \pi_s(t)s_t + \pi_e(t)e_t$, where subscripts denote partial derivatives, i.e., $\pi_s(t) \equiv \partial\pi(s_t, e_t, \theta_t)/\partial s_t$ and $\pi_e \equiv \partial\pi(s_t, e_t, \theta_t)/\partial e_t$ are the marginal products of structures and equipment, respectively. Labor is not included in the production function. When labor can be adjusted immediately at no cost, wages are equal to the marginal product of labor and all of the moments used in this paper are unchanged[2].

Given the operating profits, firms choose structures-investment, i^s, and equipment-investment, i^e, to maximize the market value of the firm. Structures and equipment evolve according to the following equations:

$$s_{t+1} = i_t^s + (1 - \delta_t^s)s_t \tag{1.1}$$

$$e_{t+1} = \gamma_t i_t^e + (1 - \delta_t^e)e_t \tag{1.2}$$

Structures at time $t+1$ is equal to investment in new structures at time t plus the non-depreciated portion of the existing stock of structures from the previous period. The accumulation of equipment, on the other hand, is subject to investment-specific technological change (as in Greenwood, Hercowitz and Krusell (2000) and Cummins and Violante (2002)). I represent the level of the technology for producing equipment as γ_t. This is typically increasing over time. Changes in gamma represent investment-specific technological change. Controlling for price, each new vintage of equipment capital tends to be more productive than the previous. To account for this change, a "new" equipment capital stock must be generated using equation (1.2) along with

[2]Merz and Yashiv include (2007) labor adjustment costs in their model. The addition of labor adjustment costs would strengthen my results. In such a case, labor adds to the value of the firm, reducing the need for large capital adjustment costs.

observed investment and an estimate of γ_t. Details are in Section 1.4.3. I assume that the proportional depreciation rates, δ_t^s and δ_t^e, vary with time.

There are costs to investing in new capital. These include direct purchase and installation costs and indirect adjustment costs. Adjustment costs include the indirect costs of installing and integrating new capital and practices. The adjustment costs function $\phi(i_t^s, s_t, i_t^e, e_t)$ is convex in each of the inputs and is homogeneous of degree one in its inputs:

$$\phi(i_t^s, s_t, i_t^e, e_t) = \phi_{is}(t)i_t^s + \phi_s(t)s_t + \phi_{ie}(t)i_t^e + \phi_e(t)e_t. \tag{1.3}$$

Both the levels of investment, i_t^s and i_t^e, and the sizes of the capital stocks, s_t and e_t, may affect the magnitude of the adjustment costs. To simplify notation, I suppress the arguments of the adjustment costs function and use $\phi(t) \equiv \phi(i_t^s, s_t, i_t^e, e_t)$ whenever possible. In addition to the cost of adjusting structures and equipment, I assume that firms incur flow operating costs each period that are proportional to the capital stocks, $f_s s_t$ and $f_e e_t$, where $f_s, f_e > 0$.

Liu, Whited, and Zhang (2007) show that when firms use both debt and equity financing, stock returns are no longer equal to simple investment returns. At the portfolio level, they find debt to be important in relating stock and investment returns. To add this element of realism to the model I include debt financing and test its importance in firm valuation. Following Hennessy and Whited (2005), I model one-period debt. At the beginning of period t, firms issue one-period debt, b_t, that must be repaid at the beginning of period $t+1$. The gross interest rate on b_t, is denoted l_t. When applying the model to the data, I treat the choice of debt as given. Because there are no taxes or bankruptcy costs, the choice of debt should not affect the firm's investment decisions.

1.2.1 Value Maximization

Managers maximize the discounted future cash flows, d_t, of the firm to the shareholders using the exogenously determined pricing kernel, $m_{t,t+\tau}$, by choosing investment in structures and equipment capital over an infinite horizon. In this case, the cum-dividend market value of equity of the firm is

$$v(s_t, e_t, b_t, \theta_t, \gamma_t) = \max_{\left\{i^s_{t+\tau}, i^e_{t+\tau}\right\}_{\tau=0}^{\infty}} E_t \left[\sum_{\tau=0}^{\infty} m_{t,t+\tau} d_{t+\tau} \right] \tag{1.4}$$

subject to

$$d_t = \pi(s_t, e_t, \theta_t) - f_s s_t - f_e e_t - \phi(i^s_t, s_t, i^e_t, e_t) + b_t - l_t b_{t-1} \tag{1.5}$$

$$s_{t+1} = (1 - \delta^s_t) s_t + i^s_t \tag{1.6}$$

$$e_{t+1} = (1 - \delta^e_t) e_t + \gamma_t i^e_t. \tag{1.7}$$

The shareholders receive the cash flow, or dividend, d_t, which consists of the revenues, $\pi(t)$, minus the flow operating costs, $f_s s_t$ and $f_e e_t$, minus the direct and indirect costs of investment, $\phi(t)$, plus the difference between the amount of debt raised, b_{t+1}, and the amount due, $l_t b_{t-1}$.

The optimality conditions which must be consistent at time t and $t+1$ are:

$$i^s_t: \quad q^s_t = \phi_{is}(t) \tag{1.8}$$

$$i^e_t: \quad q^e_t = \frac{\phi_{ie}(t)}{\gamma_t} \tag{1.9}$$

$$s_{t+1}: \quad q^s_t = E_t \left[m_{t+1} \left\{ \pi_s(t+1) - f_s - \phi_s(t+1) + (1 - \delta^s_{t+1}) q^s_{t+1} \right\} \right] \tag{1.10}$$

$$e_{t+1}: \quad q^e_t = E_t \left[m_{t+1} \left\{ \pi_e(t+1) - f_e - \phi_e(t+1) + (1 - \delta^e_{t+1}) q^e_{t+1} \right\} \right], \tag{1.11}$$

where q^s_t and q^e_t are the present-value multipliers or shadow prices associated with constraints (1.6) and (1.7), respectively. The first order conditions (1.8) and (1.9) equate the marginal costs of investing in structures capital, $\phi_{is}(t)$, and equipment capital, $\phi_{ie}(t)/\gamma_t$, with their marginal benefits, q_t^s and q_t^e. The equations (1.10) and (1.11) are the Euler equations that describe the evolution of the shadow prices of capital. Rolling equations (1.10) and (1.11) forward and recursively substituting the results, q_t^s and q_t^e can be represented as the expected present value of the marginal profit from investing in structures and equipment capital. Managers will increase investment up to the point at which the marginal costs of investment are equal to the expected marginal benefits.

Equations (1.8) and (1.9) imply that $E_t[m_{t+1}r^I_{st+1}] = E_t[m_{t+1}r^I_{et+1}] = 1$, where

$$r^I_{st+1} \equiv \frac{\pi_s(t+1) - f_s - \phi_s(t+1) + (1-\delta^s_{t+1})\phi_{is}(t+1)}{\phi_{is}(t)} \tag{1.12}$$

is the return to investing in new structures,

$$r^I_{et+1} \equiv \frac{\pi_e(t+1) - f_e - \phi_e(t+1) + (1-\delta^e_{t+1})\phi_{ie}(t+1)/\gamma_{t+1}}{\phi_{ie}(t)/\gamma_t} \tag{1.13}$$

is the return to investing in new equipment. The returns to investment in equations (1.12) and (1.13) are the ratios of the marginal benefit at time $t+1$ to marginal cost at time t .

The costs of investing in an additional unit of structures capital include the purchase price and marginal adjustment costs, both of which are represented by $\phi_{is}(t)$. The term $\pi_s(t+1) - f_s$ in the structures investment return equation is the marginal revenue minus the marginal flow operating cost from an additional unit of structures capital at time $t+1$. The term $-\phi_s(t+1)$ represents the marginal adjustment costs from an additional unit of k_{t+1}. With economies of scale in the adjustment costs function, this term will be positive. The marginal investment cost term $(1-\delta^s_{t+1})\phi_{is}(t+1)$ represents the continuation value, or shadow price at time $t+1$, net of depreciation, which can be seen by substituting using equation (1.8). Thus, the ratio of the net profits at time $t+1$ to the cost of investing at time t represents the gross investment return. The equipment investment return is analogous with the exception of the term γ_t which adjusts for the level of technology in producing equipment.

1.2.2 Market Values and Stock Returns

I use the Generalized Method of Moments procedure to estimate the model parameters and to test how well the model performs in a valuation context. I define the ex-dividend market value of equity, p_t, as

$$p_t \equiv v(s_t, e_t, b_t, \theta_t, \gamma_t) - d_t \tag{1.14}$$

and the stock return as

$$r^S_{t+1} \equiv \frac{v(s_{t+1}, e_{t+1}, b_{t+1}, \theta_{t+1}, \gamma_{t+1})}{p_t} = \frac{p_{t+1} + d_{t+1}}{p_t}. \tag{1.15}$$

Using these two definitions, the following two propositions provide two of the four moments used in the estimation procedure.

Proposition 1. (Market Value of the Firm) *Let the market value of the firm, v_t, be as in (1.4) and define the ex-dividend market value of equity, p_t, as in (1.14). Then, in equilibrium, the market value of the firm can be expressed as*

$$v_t = p_t + b_t = q^s_t s_{t+1} + q^e_t e_{t+1}. \tag{1.16}$$

Proof. See the first appendix. □

Proposition 1 states that the market value of the firm's equity and debt is equal to the value of the structures and equipment capital stocks using the shadow prices of capital investment. Note that the structures and equipment capital stocks are evaluated one period ahead. This is because capital takes one period to become productive and is determined by the optimal amount of investment at time t. The effect of investment-specific technological change is captured in q_t^e, which can be seen by plugging equation (1.9) into (1.11).

Proposition 2. (Stock Returns) *Let the market value of the firm, v_t, be as in (1.4) and define the firm's market leverage ratio, ν_t, as $\nu_t \equiv b_t/(p_t + b_t)$. Then, in equilibrium, the firm's stock and bond returns are related to investment returns as follows:*

$$\nu_t r_{t+1}^B + (1 - \nu_t)\, r_{t+1}^S = \omega_t r_{st+1}^I + (1 - \omega_t)\, r_{et+1}^I, \tag{1.17}$$

where the stock return, r_{t+1}^S is defined in (1.15), the investment returns, r_{st+1}^I and r_{et+1}^I, are defined in (1.12) and (1.13), and ω_t is defined as:

$$\omega_t \equiv \frac{q_t^s s_{t+1}}{q_t^s s_{t+1} + q_t^e e_{t+1}} = \frac{\phi_{is}(t) s_{t+1}}{\phi_{is}(t) s_{t+1} + \phi_{ie}(t) e_{t+1}}. \tag{1.18}$$

Proof. See the first appendix. □

Proposition 2 states that the leverage-weighted average of the stock and bond return is equal to the weighted average investment return. This is a generalization of the stock-investment return relation introduced by Cochrane (1991). The investment returns are weighted according to the contribution of the type of capital to total market value. These two equations are used along with the firm's first order conditions for investment to estimate the model parameters.

1.3 Econometric Methodology

1.3.1 Estimation Strategy

I use Hansen's (1982) Generalized Method of Moments (GMM) procedure to estimate seven parameters of the model. In the rational expectations framework, the firm's expectational errors for each moment, ϵ_t, should be orthogonal to the instruments, Z_t, which are in the firm's information set at the time t: $E_t[Z_t \bigotimes \epsilon_t(x_{t+1}, \Theta_0)] = 0$. In this orthogonality condition, $\bigotimes$ is the Kronecker product, x_t is a vector of data and Θ_0 is the vector of true model parameters. In the GMM framework, the best estimate of Θ_0 is that which minimizes the quadratic form using the sample counterparts to the orthogonality condition:

$$\widehat{\Theta} = \underset{\Theta}{\text{argmin}} \left(\frac{1}{T} \sum_{t=1}^{T} Z_t \bigotimes \epsilon_t(x_{t+1}, \Theta) \right)' W \left(\frac{1}{T} \sum_{t=1}^{T} Z_t \bigotimes \epsilon_t(x_{t+1}, \Theta) \right), \quad (1.19)$$

where W is a weighting matrix. The four moment conditions used in the estimation process are described below. The instruments are described in the data section.

The Investment Euler Equations

Two quantity moment conditions corresponding to the structures-investment Euler equation from combining equations (1.8) and (1.10):

$$\phi_{is}(t) = E_t \left[m_{t+1} \left(\pi_s(t+1) - f_s - \phi_s(t+1) + \phi_{is}(t+1)(1 - \delta^s_{t+1}) \right) \right] \quad (1.20)$$

and the equipment-investment Euler equation from combining equations (1.9) and (1.11):

$$\frac{\phi_{ie}(t)}{\gamma_t} = E_t \left[m_{t+1} \left(\pi_e(t+1) - f_e - \phi_e(t+1) + \frac{\phi_{ie}(t+1)}{\gamma_{t+1}} (1 - \delta^e_{t+1}) \right) \right] \quad (1.21)$$

are included in the set of moments. To induce stationarity, I scale (1.20) and (1.21) by π_t/s_t and π_t/e_t, respectively. These two equations restrict the set of possible shadow prices to those that can occur in equilibrium. On average, managers' forecasts of marginal profits from investing will equal marginal costs. Pastor and Veronesi (2006) use a reduced form model of firm profitability and do not directly use the information contained in firms' investment decisions.

The Asset Valuation Equation

Combining equations (1.10) and (1.11) with equation (1.16) and rearranging yields the valuation equation:

$$\begin{aligned}\frac{p_t}{\pi(t)} &= \frac{s_{t+1}}{\pi(t)} E_t\left[m_{t+1}\left(\pi_s(t+1) - f_s - \phi_s(t+1) + \phi_{is}(t+1)(1-\delta^s_{t+1})\right)\right] \\ &+ \frac{e_{t+1}}{\pi(t)} E_t\left[m_{t+1}\left(\pi_e(t+1) - f_e - \phi_e(t+1) + \frac{\phi_{ie}(t+1)}{\gamma_{t+1}}(1-\delta^e_{t+1})\right)\right] \\ &- \frac{b_t}{\pi(t)}.\end{aligned} \tag{1.22}$$

Prices are not stationary. In the long run, prices increase at roughly the same rate as profits. I scale the moment condition by π_t to deal with stationary variables in the estimation. Merz and Yashiv (2005) estimate a similar equation—equation (2.20)—in their paper.

The asset valuation equation allows me to study the important question as to whether the q-theoretic model can quantitatively explain the stock market "bubble" in the late 1990s as well as how different ingredients of the model contribute to the stock price run-up and subsequent decline.

The Expected Return Equation

Cochrane (1991) tests the relationship between investment returns and stock returns, which are equal in his model. In my model, the relationship is more complex. To further restrict the set of parameter values allowed by my model, I include in my set of moment conditions the following expected-return equation implied from equation (1.17):

$$E\left[r^S_{t+1} - \frac{\omega_t r^I_{st+1} + (1-\omega_t) r^I_{et+1} - \nu_t r^B_{t+1}}{1-\nu_t}\right] = 0. \tag{1.23}$$

This relation holds with or without expectations. Note that Merz and Yashiv (2005) do not estimate the return moment condition. The second term in the brackets is the levered investment return. Liu, Whited and Zhang (2007) implement this equation in the cross-section of returns.

1.3.2 Functional Forms

The production function is Cobb-Douglas, $\pi(s_t, e_t, \theta_t) = A(\theta_t) s_t^{\alpha} e_t^{1-\alpha}$, which exhibits constant returns to scale. Its partial derivatives are

$$\pi_s(t) = \alpha \frac{\pi(s_t, e_t, \theta_t)}{s_t} \tag{1.24}$$

$$\pi_e(t) = (1-\alpha) \frac{\pi(s_t, e_t, \theta_t)}{e_t}, \tag{1.25}$$

with α and $(1-\alpha)$ denoting the output elasticities of structures and equipment, respectively. I estimate α. The linear homogeneous adjustment costs function allows costs to vary across the two types of capital:

$$\phi(i^s_t, s_t, i^e_t, e_t) = i^s_t + i^e_t + \left(a_s \frac{i^s_t}{s_t}\right)^{\eta_s} s_t + \left(a_e \frac{\gamma_t i^e_t}{e_t}\right)^{\eta_e} e_t. \tag{1.26}$$

Over the relevant parameter space, adjustment costs are increasing in investment, i^s_t and i^e_t, and decreasing in the capital stocks, s_t and e_t. For the same level of investment, larger firms incur smaller adjustment costs. The coefficients, a_s and a_e, are scale parameters to be estimated. These functions are typically assumed to be quadratic, but following Merz and Yashiv (2007), I estimate the powers of the adjustment costs function, η_s and η_e, and test the importance of this assumption. In the quadratic case, marginal adjustment costs are linear in investment-capital ratios. With powers greater than 2, this relationship is convex. Because q_t^s and q_t^e are equal to marginal adjustment costs in equilibrium, increasing the powers of the adjustment costs function will magnify the variability the investment-capital ratios, and in turn, the variability of implied returns.

The power parameters of the adjustment cost function provide measures of the elasticities of the indirect portions of q_t^s and q_t^e with respect to changes in investment. In particular, it can be shown that

$$\frac{\partial(q_t^s - 1)/(q_t^s - 1)}{\partial i_t^s / i_t^s} = \eta^s - 1 \tag{1.27}$$

and

$$\frac{\partial(q_t^e - 1)/(q_t^e - 1)}{\partial i_t^e / i_t^e} = \eta^e - 1. \tag{1.28}$$

So, in the standard quadratic adjustment costs case, a one percent increase in investment is associated with a one percent increase in the portion of q_t attributable to the indirect adjustment costs.

1.3.3 Diagnostics

After estimating the production function parameter, the two operating cost parameters, and the four adjustment costs parameters, I use a variety of diagnostic tests to evaluate the model performance along several important dimensions.

Prices

The main aim of the paper is to apply a neoclassical q-theory model to firm valuation. I estimate the model parameters with and without investment-specific technological change for both sectors. After estimating the parameters, the predicted market value of equity is compared to the observed value. Next, to evaluate the importance of each of the main elements of the model, I estimate several alternate specifications and examine the resulting price levels. In particular, I estimate parameters for the following variations: homogeneous capital, no leverage, and quadratic adjustment costs. Finally, I divide the US corporate nonfinancial series into two subsamples and repeat the estimation.

Model Fit

In the GMM framework, when there are more equations than parameters, the quadratic form on the right hand side of (1.19) will be greater than zero. The test of overidentifying restrictions is a test of the overall fit of the model. In particular, defining J_T as the minimized value of the right hand side with an optimal weighting matrix, W^*,

$$J_t = \left(\frac{1}{T} \sum_{t=1}^{T} Z_t \bigotimes \epsilon_t(x_{t+1}, \widehat{\Theta}) \right)' W^* \left(\frac{1}{T} \sum_{t=1}^{T} Z_t \bigotimes \epsilon_t(x_{t+1}, \widehat{\Theta}) \right),$$

then $TJ_T \sim \chi^2(\#moments \times \#instruments - \#parameters)$. If this quantity is large enough, then we can reject that the model fits the data in a statistical sense. On the other hand, if this number is sufficiently close to zero, then we will fail to reject the model.

Adjustment Costs

In the standard model with no indirect adjustment costs, growth options, or intangible capital, the price of capital is equal to one and the value of the firm is equal to the value of its assets in place. Once indirect adjustment costs are added, this is no longer the case. Given the estimated parameters, time series of total adjustment costs and marginal adjustment costs are generated for the preferred models. These costs are examined for plausibility.

Stock Returns and Investment Returns

As shown in Cochrane (1991, Table I), aggregate investment returns generated using a standard q-theory model with quadratic capital adjustment costs are much less volatile than aggregate stock market returns. A natural test is whether a richer model can deliver stock market volatilities comparable to those observed in the data. Specifically, having estimated the model parameters, I compare the investment return volatility to the stock market return volatility. Additionally, the autocorrelation structures of the investment returns and investment-capital ratios are compared with those of the stock returns. Finally, correlations are calculated between stock returns and investment returns, investment growth and growth in profits as in Cochrane (1991).

1.4 Data and Summary Statistics

1.4.1 US Corporate Nonfinancial

I use quarterly data from the period 1953:1 to 2005:2 for the nonfinancial corporate business sector of the United States.

Output and Price Deflator

As my measure of output, π, I use the real value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce and its associated price deflator.

Investment, Capital, Depreciation and the Price of Investment

I require the quarterly data to conform to the annual data. This is a multi-step procedure. First, I generate quarterly investment and depreciation data for aggregate physical capital that are consistent with the annual data. Next, the quarterly investment data are separated into investment in structures and investment in equipment. Finally, I generate the quarterly structures and quarterly equipment capital stocks using the quarterly investment data and the annual depreciation data. All data are from the BEA NIPA tables and the Federal Reserve Flow of Funds data. See the data appendix for details.

Market Value of Equity and Leverage

I use the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) as my measure of the market value of equity, p_t. In the measure of financial leverage, ω_t, I use total value of credit market instruments, b_t, for nonfarm nonfinancial corporate business from the Federal Reserve (Table B.102, series FL104104005.Q) and the market value of equity.

Discount Factor and Stock and Bond Returns

Following Merz and Yashiv (2007), I use $1/r^S_{t+1}$ as the pricing kernel, $m_{t,t+1}$. In this case, r^S_{t+1} is the CRSP Value Weighted NYSE, NASDAQ and Amex nominal, gross return deflated by the inflation rate. For the bond return, r^B_t, I use the Baa-rated bond yield from the Federal Reserve of St. Louis. Stock and Bond returns are measured from point to point, and macroeconomic variables are typically quarterly averages. Following Cochrane (1996), I average monthly returns and adjust the timing so that they cover the period from the middle of the initial quarter through the middle of the following quarter.

1.4.2 NASDAQ data

I use quarterly aggregate NASDAQ data from 1983:4 to 2005:3. The beginning of the sample is limited by the availability of disaggregated firm level investment data.

Accounting Data

The historical exchange codes in the CRSP monthly file are used to determine when stocks were listed and delisted from the NASDAQ exchange. Accounting data are gathered for those firms which are included in Compustat. Sales, capital stocks, investment, and depreciation are gathered from CRSP[3]. Total investment in fixed capital is reported quarterly, but is only disaggregated into structures and equipment annually. For each stock, I divide quarterly total investment into its two components based on the industry averages from the BEA NIPA fixed asset tables. Data are aggregated based on market value of equity. See the data appendix for more details.

Returns, Market Value of Equity and Leverage and Pricing Kernel

The total market value of securities used in the NASDAQ index (usdval) is defined as the Market Value of Equity, p_t. The value-weighted stock return including dividends, r_t^S, is taken from the indices file (vwretd) and adjusted for timing as in Cochrane (1996). As a proxy for the return to the debt, r_t^B, I use the Baa-rated bond yield from the Federal Reserve of St. Louis.

Financial leverage, ω_t, is calculated using aggregate book value of Long Term Debt from the Compustat Industrial Quarterly file (data51), and the market value of equity. Firm debt data are aggregated in the same manner as the other series.

As in the case of the aggregate US corporate nonfinancial sector, I use the CRSP value weighted index as a proxy for the pricing kernel.

[3]As in Love (2003) and Liu, Whited and Zhang (2007), sales are used in the marginal product of capital. This can be done if the production function exhibits constant returns to scale and the shocks to profits are reflected in sales.

1.4.3 Investment-Specific Technological Change

The productive quality of equipment and software may change over time, even adjusting for inflation. A common example used to illustrate this change is "Moore's Law" which states that the number of transistors that can be inexpensively placed on an integrated chip doubles approximately every two years. As long as the price of the chips increases at a lower rate than the productivity, then the real price of a chip will underestimate the level of technology embodied in the new vintage of hardware.

To model the change in the technology in producing equipment and software, I follow Greenwood, et al, (1997), and Cummins and Violante (2002), and use an exogenously determined process for γ_t based on Gordon's (1990) quality-adjusted prices for 22 categories of durable equipment from 1947-1983. Gordon estimates quality adjusted prices using price hedonic regressions. Using Gordon's indexes, Cummins and Violante measure the quality bias implicit in the NIPA price indexes for the 1947-1983 period and extrapolate the bias using the NIPA data from 1984-2000. I repeat the exercise and extend each series through 2006. Using the Tornqvist procedure[4], I aggregate the asset-level price indexes into a structures and equipment index, p_t^G. The level of technology is then calculated as $\gamma_t = p_t^C / p_t^G$, where p_t^C is a constant-quality price index for consumption constructed by applying the Tornqvist procedure to NIPA data on prices and shares of the consumption of non-durable goods (excluding energy expenditures) and nonhousing services. The quality adjusted price, p_t^G and the level of technology, γ_t for the period 1947-2006 are presented in Panels A and B of figure 1.5.

Because old equipment loses some of its value as technology improves, depreciation

[4] The Tornqvist procedure is used to form a moving-weight average of percentage growth weights. In this case, the Tornqvist index is a cumulative exponential index of growth rates in prices, where the individual weights are the shares of either the investment good, or consumption good

is adjusted according to the change in the relative price of the asset:

$$\delta_t^{e\gamma} = 1 - (1 - \delta_t^e)\frac{\gamma_{t-1}}{\gamma_t}. \tag{1.29}$$

Finally, to capture the effect of technological change on the capital stock, a new equipment series, e_t^γ is generated using the observed investment, i_t^e the adjusted depreciation, $\delta_t^{e\gamma}$, the level of technology, γ_t, and the capital accumulation equation. The new capital stock series is initialized at the beginning of the sample using steady-state levels of the equipment capital stock. Panels C and D of Figure 1.5 show the proportion of aggregate capital made up of equipment for both the US corporate nonfinancial and NASDAQ sectors. Equipment capital has become relatively more important in both cases, especially when controlling for investment-specific technological change.

1.4.4 Instruments

I use five instrumental variables in the GMM estimation which have been shown to have power in predicting prices, returns and output. The default premium, def_t, is defined as the difference between the yields of Aaa and Baa corporate bonds. The term premium, $term_t$, is the yield on ten-year notes minus that on three-month Treasury bills. Corporate bond data are from Ibbotson's index of Long Term Corporate bonds. The risk free rate, rf_t, is from Ken French's website. The equally weighted aggregate dividend yield, div_t, is from CRSP. Finally, I use the Lettau and Ludvigsen consumption-to-wealth ratio, cay_t.

1.4.5 Summary Statistics

Table 1.1 summarizes the data for the US corporate nonfinancial sector from 1953-2005 and for the NASDAQ from 1983-2005. Structures investment-capital ratios are much smaller on average than equipment ratios in both sectors. Adjusting for investment-specific technological change decreases the difference between the two, mainly because the generated equipment capital stock is larger than the observed stock. Investment in equipment is also more volatile than structures investment which will also lead to a more volatile shadow price of equipment via the adjustment costs function. Investment-capital ratios are higher in the NASDAQ for every category. On average, from 1953 to 2005, the US corporate nonfinancial sector uses more structures than equipment. The average equipment to total fixed capital ratio is 33% increases in almost every quarter, ranging between 23% in the first quarter of 1953 to 45% in the second quarter of 2005. After generating a constant quality equipment capital stock series using investment specific technological change, the average drops to 19% and the series ranges between 6% and 51%. A graph of both series is presented in Panel C of figure 1.5. The NASDAQ firms use more equipment capital than structures capital for most of the sample. On average, equipment makes up 56% of fixed capital, and ranges from a low of 49% in the fourth quarter of 1983 to a high of 63% during the first quarter of 1999. Controlling for investment-specific technological change, equipment makes up 61% of fixed capital on average and ranges between 48% and 77%. These two series are shown in figure 1.5, Panel D. Equipment depreciates more than twice as fast as structures. Once adjusting for changes in the quality of equipment capital, this difference is even larger. The table also shows that the NASDAQ firms use less debt on average, 17.1%, than the average US nonfinancial firms, 35.3%. The scaled price levels of the US corporate nonfinancial and NASDAQ sectors are roughly the same on average – price is equal to about 5.5 times output. The NASDAQ series, however, is much more volatile. As can be seen in Figure 1.6, the two series mimic each other very closely during the 1983-2005 period with the exception of the extremely high NASDAQ prices from 1999-2001.

1.5 Results

1.5.1 Valuation

To test how well the neoclassical q-theory model performs in the valuation of equity, I use the GMM framework to estimate the parameters for the generalized model with and without investment-specific technological change for both sectors and examine the parameter estimates and fit along with the predicted price levels. Then, to determine which components of the model are necessary, I add each of the following assumptions individually: homogeneous capital, equity-only financing, and quadratic adjustment costs. Finally, to test for parameter instability, I estimate the model for the US corporate nonfinancial sector for two subperiods.

Table 1.2 presents the parameter estimates and model fit for both sectors for the generalized model with and without investment-specific technological change. Panel A presents the results for the US corporate nonfinancial sector while Panel B presents those of the NASDAQ sector. For each sector, the model is estimated with and without ($\gamma_t = 1$) investment-specific technological change. Only in the US corporate nonfinancial sector with investment-specific technological change are the structures adjustment costs nontrivial. In the three other cases, the adjustment costs for structures are essentially zero. When this is the case, the standard errors for the structures adjustment cost parameters are relatively large. This is because when adjustment costs are very small, the curvature of the function is irrelevant. In these three cases, the parameter s is set to zero, the structures power parameter is ignored and the remaining five parameters are estimated. In each of these cases, the remaining parameters are relatively stable.

In all of the models, the p-value for the J_T test of overidentifying restrictions is greater than 5%. In other words, the model is not rejected at the 5% level of significance. The fit is especially good in the NASDAQ sector. In all four specifications, the structures output elasticity, α, is close to one. All of the estimated equipment adjustment cost powers, η_e, are greater than 2, suggesting that the quadratic adjustment costs specification is not necessarily the best choice at the aggregate level. These parameters are all smaller with investment-specific technological change than without. The equipment adjustment costs power parameter ranges from 5.45 to 6.54 on the US corporate nonfinancial sector and from 2.18 to 3.68 on the NASDAQ. The coefficients of the adjustment costs function, a_s and a_e, are relatively stable for each sector. Evaluating the marginal adjustment costs at the mean investment-capital ratios from Table 1.1 provides intuition as to the economic significance of the magnitude of these coefficients. In equilibrium, these are equal to the present value of the expected marginal profits from investing, q_t^s and q_t^e. For the US corporate nonfinancial sector, the "average" marginal investment costs for structures without and with investment-specific technological change are 1.00 and 1.39 per dollar invested. The corresponding costs for equipment are 1.69 and 1.58 per dollar. In the NASDAQ sector, the "average" costs are 1.00 and 1.00 for structures and 9.08 and 7.33 for equipment. In a model without indirect adjustment costs, these values are all equal to 1 and the value of the firm is equal to the value of assets in place. When it is costly to invest, managers will only do so if they expect marginal cash flows to be sufficiently high. In this case, the marginal cash flows, or shadow prices of equipment, are much higher on average on the NASDAQ than for the US corporate nonfinancial sector.

Using the asset valuation equation (1.22) and the parameter estimates from Table 1.2, a price series can be generated for all four models and compared to the actual prices observed in the market. Panel A of Figure 1.7 presents the resulting graphs for the US corporate nonfinancial sector for both specifications – with and without investment-specific technological change. In the latter case, the model with the restriction $a_s = 0$ is used, although the price series in the other looks very similar.

Both predicted price series are slightly lower than the actual series from about 1958 until about 1973, and both are slightly higher during 1977 through about 1986. From 1986 until the end of the sample, the model with no investment-specific technological change does a good job of matching the observed levels with the exception of the extremely high prices during the peak of the "bubble" during the year 2000. Once equipment capital is adjusted for changes in quality, the model is able to match even the these extremely high prices. However, this second model produces prices that are much too high starting in about 2003. By the end of the sample, the predicted prices are roughly double those observed in the market. Panel B presents the results for the NASDAQ models. Again the models with the restriction $a_s = 0$ are used, but the plots for the model without this restriction look almost identical. The model without investment-specific technological change overvalues the equity in almost every quarter until the 4th quarter of 1998. After the 2nd quarter of 2001, it undervalues the equity relative to the market. In the intermediate period it is roughly able to replicate the extreme run up and decline in prices with the exception of the most extreme quarter – the 2nd quarter of 2000. With the introduction of investment-specific technological change to the model, the fit improves drastically over the entire length of the sample. With the exception of the most extreme quarter of the "bubble" period, the model fits the data very well.

1.5.2 Adjustment Costs

When adjustment costs are convex, managers increase investment until the marginal costs of investing equal the present value of the expected marginal profits from investing. In equilibrium, investment is relatively high when rational managers expect marginal profits to be relatively high. When the present value of marginal profits is high, firm value is high. Figure 1.9 shows time series of equipment investment-capital ratios, i_t^e/e_t, and shadow prices of equipment, q_t^e, for both sectors. In equilibrium, the latter is equal to the marginal costs of investment in equipment. When adjustment costs are quadratic, marginal costs are a linear function of investment-capital ratios. In our case, the relation is convex. Panel A shows the two time series for the US corporate sector without investment-specific technological change. In a relative sense, the investment-capital ratio mimics the price time series. Mechanically, when investment is relatively high, adjustment costs are relatively high. In equilibrium, marginal costs of investment are equal to marginal returns from investing. Intuitively, when the present value of the marginal profits from investing in new capital is relatively high, managers will increase investment and the value of the firm, $V_t = q_t^s s_{t+1} + q_t^e e_{t+1}$, will be relatively high. The main driving forces behind the price series from the model are the structures and equipment investment-capital ratios, which determine q_t^s and q_t^e.

One way to determine how reasonable the adjustment costs parameters are is to examine the implied adjustment costs and shadow prices, which are equal to the marginal capital adjustment costs. The adjustment costs function includes the purchase price of the capital along with the costs of adjustment. Table 1.3 presents time series averages and standard deviations of adjustment costs as a percentage of total output, net of direct investment costs, $(\phi_t - i_t^s - i_t^e)/\pi_t$, and the shadow prices of capital investment, q_t^s and q_t^e. For the US corporate nonfinancial sector in Panel A, the average adjustment costs as a percentage of output ranges from 2% to 2.5%. This is much smaller than the 4.2% reported by Merz and Yashiv (2005) when treating capital as homogeneous for the same sector. The corresponding ratios for the NASDAQ (Panel B) are between 9.6% and 13.8%, which is much higher than the numbers found in Merz and Yashiv (2005). However, they do not fit their model using NASDAQ data. The NASDAQ is more heavily weighted towards equipment than towards structures. Part of the reason for the increase is that equipment capital is more costly to adjust. Lichtenberg (1988) finds that an increase in capital investment of one dollar decreases current output by 35 cents on average. He also finds evidence to suggest that the marginal costs of adjusting equipment are larger than those associated with structures. For the US nonfinancial sector, the time series average marginal costs of investment in structures, q_t^s, varies between 1.000 and 1.364 and the average marginal cost of investment in equipment, q_t^e, ranges from 1.954 to 2.119. NASDAQ estimates in Panel B are 1.000 and 1.000 for structures and are much higher for equipment – between 6.045 and 9.789. The marginal costs for the model that best fits the price time series are 1.000 for structures and 7.331 for equipment. Based on previous estimates, these costs seem plausible. Merz and Yashiv (2005) include a survey of past estimates of total marginal adjustment costs, excluding the direct marginal costs of investment. Adjusting for direct costs, past estimates of the average marginal adjustment costs range between 1.02 and 10.47. These estimates do not distinguish between types of capital. Because the adjustment costs for homogeneous capital would be a convex combination of the costs for structures and equipment, the marginal costs of adjusting equipment are an upper bound. The time series of q_t^s and q_t^e for the two preferred models – without investment-specific technological change for the US sector and with this change for the NASDAQ – can be seen in Figure 1.8.

When capital is divided into structures and equipment, and the adjustment costs function is allowed to be non-quadratic, the q-theory model does a good job of valuing aggregate US corporate nonfinancial equity and the NASDAQ sector – especially from the mid-1990s through 2005. Investment-specific technological change improves valuation in the NASDAQ sector, but does not seem to be as important in the US corporate nonfinancial sector. Both average and marginal adjustment costs are reasonably small based on the past literature.

1.5.3 Alternative Specifications

To determine which of the elements of the generalized model are necessary, I start with the two preferred models from Table 1.2 – the generalized model without investment-specific technological change for the US corporate nonfinancial sector, and the model that includes this technological change in the NASDAQ sector – and add the following assumptions individually: homogeneous capital, equity only financing, and quadratic adjustment costs. Then, I examine the parameter estimates and model fit and plot the time series of predicted price levels. Finally, I test for parameter instability in the US corporate nonfinancial sector with a subsample analysis.

Single Capital Good

To evaluate the importance of separating fixed capital into structures and equipment, I treat all capital as homogeneous, estimate the parameters, and examine the fit. The three moments that are used in the GMM estimation procedure are

$$\phi_i(t) = E_t \left[m_{t+1} \left(\pi_k(t+1) - c - \phi_k(t+1) + \phi_i(t+1)(1-\delta_{t+1}) \right) \right] \tag{1.30}$$

$$\frac{p_t}{\pi_t} = \frac{k_{t+1}}{\pi_t} E_t \left[m_{t+1} \left(\begin{array}{c} \pi_k(t+1) - c - \phi_k(t+1) \\ +\phi_i(t+1)(1-\delta_{t+1}) \end{array} \right) \right] - \frac{b_t}{\pi_t} \tag{1.31}$$

$$0 = E \left[r^S_{t+1} - \frac{r^I_{t+1} - \nu_t r^B_{t+1}}{1-\nu_t} \right] \tag{1.32}$$

These are the first order condition for investment in total fixed capital, k_t, the asset valuation equation, and the stock-investment returns identity for the single capital goods case. Before estimating, the first order condition is scaled by π_t/k_t to help deal with stationarity issues. The estimated parameters and model fit for the homogeneous capital case using the US corporate nonfinancial data series are presented in Panel A of Table 1.4. As in the case of multiple capital goods, the adjustment costs function is non-quadratic with a power parameter of 7.14. Panel A of Figure 1.10 plots the actual scaled equity price versus the predicted prices from the preferred model and the model with a single capital good with leverage. The two models perform similarly until the "bubble" period in which case separating capital into two components seems to help explain the high prices. Panel B of Table 1.4 shows that the model with homogeneous capital fits the mean NASDAQ moments well. With homogeneous capital, the adjustment costs power parameter is between 2.54 and 2.76. Panel B of Figure 1.10 shows that while the prices predicted by the model with a single capital good match those of the model with heterogeneous capital at the peak of the bubble, it comes at the expense of a poor fit for the rest of the sample. By the end of the sample, the model generated prices are one-third as large as those observed in the market.

All Equity

For simplicity, it may be convenient to treat a firm's financing as equity only as done in Cochrane (1991). This is a common assumption when examining the link between investment returns and stock returns. However, it may not make much sense in the valuation context where absolute levels are needed. For example, in the US corporate nonfinancial sector, the value of the fixed capital exceeds the market value of equity. Any adjustment costs will increase this difference. On average, the US nonfinancial sector has a leverage ratio of 35% compared to 17.1% for the NASDAQ. Because NASDAQ firms use much less debt, I focus my energy on that sector. To test the importance of leverage in valuation, I assume that firms have no debt ($b_t = 0$) and repeat the GMM estimation with the same moment conditions and instruments as in the general case and then compare the predicted price levels to those from the preferred model. Again, investment-specific technological change is included in the NASDAQ case. The first column of Panel B in Table 1.5 shows the parameter estimates and overall fit for the NASDAQ in the all equity case. As was the case in the generalized model, the adjustment costs coefficient for structures, a_s, is very close to zero. This causes problems when estimating the associated power parameter. As a result, I set the a_s to zero and estimate the model a second time. The power parameter for the equipment is 2.43 which is larger in than in the preferred model which included debt. The overall fit of the model is very good with a p-value of 0.921. From Panel B of Figure 1.11, we see that the predicted price series for both the preferred model and the all equity model do very well at fitting the market data for most of the sample. In fact, with the exception of four quarters during 2000 and 2001, the two are almost indistinguishable. Thus, at least in terms of relative valuation, leverage does not seem to be a crucial ingredient in pricing the NASDAQ over the course of this sample.

Quadratic Adjustment Costs

Many models assume adjustment costs functions to be quadratic. In such a case, marginal costs are linear in investment-capital ratios. As shown in the general case, this may not be ideal at the aggregate level. However, imposing this assumption may aid in estimation by reducing the number of parameters. As before, the assumption is imposed on the preferred specifications from the generalized model, and the results examined and compared. The second column of Panel A in Table 1.5 presents the results of the quadratic adjustment costs case for the US corporate nonfinancial sector. With this added assumption, the p-value for the overall fit is 0.13 and the estimated adjustment costs coefficients are 1.18 for structures and 3.43 for equipment. As seen in Panel A of Figure 1.11, the prices behave much the same as those predicted by the preferred model until the mid-90s during which time they significantly undervalue the equity. They are not able to match the high prices observed during this period.

When quadratic adjustment costs are used in the NASDAQ, as seen in the second column of Panel B, Table 1.5, the fit is very good. In the preferred case, the equipment adjustment costs were close to quadratic with a power parameter of 2.19, and the marginal structures adjustment costs - net of the direct investment costs - were essentially zero, so we might expect the model to perform relatively well. The structures adjustment costs coefficient is 1.10, but is not significantly different from zero. The equipment adjustment costs coefficient is 8.04 which is more than twice as large as the coefficient in the aggregate US case. In Panel B of Figure 1.11 we see that the quadratic adjustment costs model does almost as well as the preferred model in pricing the equity for most of the sample. It does produce a run up in prices during the bubble period, but they are not quite as great as those predicted by the model with non-quadratic costs.

Subsample Analysis

It is possible that the poor fit in the early part of the sample in the US corporate nonfinancial sector is due to parameter instability. If the parameters of the underlying adjustment costs function, or profit function are changing over time, the model is not likely to do well over the entire sample. For example, the structures capital share decreases in almost every quarter, which suggest that its output elasticity might also be changing with time. To test for this, I split the sample in half, from the 1st quarter of 1953 through the 1st quarter of 1979, and from the 2nd quarter of 1979 through the 2nd quarter of 2005. In Table 1.6, I present results for two specifications – with and without investment-specific technological change – for each subsample. The fit of all four models improves relative to the results from the entire sample. The structures elasticity of output, α is much lower over the first part of the sample than the second. The power parameters for structures are between 3.74 and 3.87 during the first subperiod and 2.34 in the second subperiod. In each case, the structures parameter is less precisely estimated, but larger than the corresponding equipment parameter. In the first subperiod, investment-specific technological change seems to improve the overall fit. This is not the case in the second subperiod. However, because two more parameters, a_s and η_s, are estimated, the degrees of freedom are smaller. From the plots in Figure 1.13, we can see the results of breaking the sample into two parts and estimating each separately on valuation. Without investment-specific technological change, Panel A, there does not seem to be a significant change. Once investment-specific technological change in included, Panel B, the story changes slightly. In the first subsample, the fit is much the same for the first third, slightly better in the middle, and slightly worse at the end. For the second subsample, the fit is slightly better for the first 6 years and slightly worse for the next decade. For the "bubble" period – from about 1995 through about 2003, the model using the subsample does a very good job of fitting the observed data. The second subsample roughly corresponds to the period covered in the Merz and Yashiv (2007) study. It still suffers from the same end of sample problem that we see in the model using the full sample, but the overpricing is slightly lower. Overall, breaking the sample into two periods and estimating each separately did little to improve the fit in terms of the time series of prices.

1.5.4 Stock and Investment Returns

As shown by Cochrane (1991), the investment returns from a q-theory model with quadratic adjustment costs, homogeneous capital and no debt are much less volatile than market stock returns. In particular, he estimates the quarterly standard deviation of investment returns to be 3.42% compared to the market return volatility of 7.24% for the period from 1947–1987. In standard q-theory models, investment returns are exactly equal to stock returns. In the model in this paper, the stock return is equal to the levered investment return as in (1.23). Figure 1.14 plots these returns against the real stock returns for the US corporate sector and the NASDAQ sector using the preferred models.

Volatilities

The relation between stock returns and investment returns in Proposition 2 holds state-by-state. In addition to the first moment holding, all higher moments should hold. The second moment is not included in the GMM estimation procedure. A natural test is whether a richer model can deliver stock market volatilities comparable to those observed in the data. I use the aggregate US corporate nonfinancial levered investment returns predicted by the preferred model without investment-specific technological change, and the investment returns predicted by the NASDAQ model with investment-specific technological change and calculate means, standard deviations, and autocorrelations. Tables 1.7 and 1.8 include these estimates along with means, standard deviations and autocorrelations of the investment capital ratios and the CRSP value weighted real stock return.

For the US corporate nonfinancial sector, the standard deviation of the stock return for the period from 1953–2005 is 6.41%, which is very close to the standard deviation of the investment return of 6.13%. Consistent with Cochrane (1991, Table I), the investment returns are more positively autocorrelated than the stock returns. The 1-quarter autocorrelation of the stock return is 0.33 compared to 0.55 for the investment return. The investment-capital ratios have high positive autocorrelations.

The NASDAQ returns are more volatile than those for the US corporate sector. The levered investment returns from the model are even more volatile. The model produces a quarterly standard deviation of returns of 12.63% compared to the observed standard deviation of 10.44%. Liu, Whited and Zhang (2007) found the monthly levered investment return volatility to be smaller than the observed stock return volatility in 24 of the 25 Fama-French size and book-to-market portfolios. They use a neoclassical model similar to mine. However, they do not consider non-quadratic adjustment costs or multiple capital goods.

To better understand the source of the model's ability to generate higher volatilities than that of previous models, I calculate standard deviations from the predicted stock returns for each specification and present the results in Table 1.9. Each specification represents the change in one model assumption. However, because all of the model parameters change for each specification, it is difficult to attribute the changes in standard deviations to any one parameter. The various models produce a wide range of standard deviations. The first column of Table 1.9 presents results for the US corporate nonfinancial sector. Cochrane (1991) uses homogeneous capital, equity only financing and quadratic adjustment costs in the US corporate sector and generates standard deviations of less than half the size of those observed. Three of the specifications represent these three assumptions individually. In each of these three cases, the predicted standard deviations are much lower than the observed value. The model with homogeneous capital and the model with equity-only financing generate stock return standard deviations of about 2.5% per quarter compared to the actual value of 6.41%. Restricting adjustment costs to be quadratic in investment results in quarterly standard deviations of 4.32%. In the general case, with and without investment-specific technological change, predicted returns are roughly as volatile as actual returns at 6.32% and 6.13%, respectively.

At the aggregate NASDAQ level, it is much easier to generate high stock return volatilities. Within the framework of the model, return volatility is driven principally by volatility in marginal revenues and marginal costs, which in turn are driven by investment-capital ratios and output. As shown in Table 1.1, the NASDAQ investment capital ratios are much more volatile than those of the US corporate nonfinancial sector, with standard deviations of 1.31% versus 0.18% for the structures series and 1.64% versus 0.75% for the equipment series. Once investment-specific technological change is added the standard deviations of the investment capital ratios for equipment become 1.65% for the NASDAQ and 1.06% for the US corporate nonfinancial sector. This disparity carries through to the predicted stock return series. As shown in the second column of Table 1.9, all of the models produce stock returns that are at least as volatile as observed returns. The standard deviation of returns in the quadratic adjustment costs case, 10.8% per quarter, is the closest to the actual value of 10.36%. The standard deviations generated by the other specifications range from 11.53% in the all-equity case to 18.70% in the generalized model without investment-specific technological change. It is not clear how these specifications would compare if the second moment were included in the GMM estimation procedure.

Correlations

In Table 1.10, the correlation between stock returns and model generated levered investment returns is estimated. For the US corporate nonfinancial sector, there is some positive correlation between the equipment investment return and the stock return, but virtually none between the levered investment return. For the NASDAQ, however, there is a strong, statistically significant relation between the two. The correlation between the actual and predicted stock return is 0.37 and is highly significant. Table 1.10 also presents correlations between stock returns and investment growth and growth in output. Growth in investment and output are highly correlated with US corporate nonfinancial stock returns. Structures investment growth and growth in output are not significantly correlated with the NASDAQ stock return index.

1.6 Adjustment Costs and Human Capital Accumulation

Fixed capital loses much of its productive capacity when it used improperly. The amount of knowledge required to effectively use capital varies. It may take very little effort to learn the best way to dig a hole with a new shovel or to learn to unlock a door. On the other hand, many hours may be required to learn how to effectively utilize a new computer program or operate a complex machine. Investment in new capital —

especially high technology capital — is often accompanied by unmeasured investment in human capital. Workers who would otherwise be producing goods and services spend time learning how to use newly acquired equipment and software. If labor is not disaggregated into time spent producing and time spent learning, measured productivity will decrease when investment is high. This should be especially true where large amounts of human capital are required.

To examine whether some of the adjustment costs measured in the previous sections are proxies for human capital accumulation, consider the following model. The firm uses structures, s_t, equipment, e_t, labor, l_t, and human capital, h_t, to produce output, π_t, as follows:

$$\pi_t = A_t s_t^{\alpha_s} k(e_t, h_t)^{\alpha_e} (\theta_t^{\pi} l_t)^{1-\alpha_s-\alpha_e}. \tag{1.33}$$

Here, θ_t^{π} is the fraction of observed labor hours dedicated to producing output and A_t is the time varying total factor productivity which has the following process:

$$A_t = A_{t-1} e^{g+\varepsilon_t}, \tag{1.34}$$

where g is the mean growth rate of A_t and $\varepsilon_t \sim iid$ and mean zero. The function $k(e_t, h_t)$ relates the use of equipment and human capital. For simplicity, I assume that the two are perfect complements[5]:

$$k(e_t, h_t) = min(e_t, \nu h_t). \tag{1.35}$$

With this Leontief production function, equipment and human capital will be optimally used in fixed proportions. The structures, equipment and human capital stocks

[5] A more general CES production function with a low elasticity of substitution will generate the same qualitative predictions.

evolve according to the familiar one period dynamics:

$$s_{t+1} = (1-\delta^s)s_t + i_t^s \tag{1.36}$$

$$e_{t+1} = (1-\delta^e)e_t + i_t^e \tag{1.37}$$

$$h_{t+1} = (1-\delta^h)h_t + i_t^h. \tag{1.38}$$

In practice, we can observe capital stocks, depreciation rates, and investment in structures and equipment. However, we cannot directly observe human capital or investment in human capital. I model investment in human capital as a production process that requires labor input:

$$i_t^h = B_t(1-\theta_t^\pi)l_t, \tag{1.39}$$

where B_t is the level of productivity in producing human capital. Dividing π_t by l_t and taking log differences, we get the growth of output per labor hour:

$$\begin{aligned} &log\left(\frac{\pi_t/l_t}{\pi_{t-1}/l_{t-1}}\right) \\ &\quad = g + \varepsilon_t + \alpha_s log\left(\frac{s_t/l_t}{s_{t-1}/l_{t-1}}\right) + \alpha_e log\left(\frac{e_t/l_t}{e_{t-1}/l_{t-1}}\right) + (1-\alpha_s-\alpha_e)log\left(\frac{\theta_t^\pi}{\theta_{t-1}^\pi}\right). \end{aligned} \tag{1.40}$$

We can observe all of the variables except for ε_t and θ_t^π. Though we cannot observe θ_t^π directly, we can test for its influence on the estimated growth rate of total factor productivity:

$$\widehat{g}_t \equiv log\left(\frac{\pi_t/l_t}{\pi_{t-1}/l_{t-1}}\right) - \widehat{\alpha}_s log\left(\frac{s_t/l_t}{s_{t-1}/l_{t-1}}\right) - \widehat{\alpha}_e log\left(\frac{e_t/l_t}{e_{t-1}/l_{t-1}}\right), \tag{1.41}$$

where $\widehat{\alpha}_s$ and $\widehat{\alpha}_e$ are regression coefficients from the following (misspecified) equation

$$log\left(\frac{\pi_t/l_t}{\pi_{t-1}/l_{t-1}}\right) = g + \alpha_s log\left(\frac{s_t/l_t}{s_{t-1}/l_{t-1}}\right) + \alpha_e log\left(\frac{e_t/l_t}{e_{t-1}/l_{t-1}}\right) + \epsilon_t. \quad (1.42)$$

Because the growth rate of θ_t^π was omitted from the regression, the estimate $\widehat{g}_t$ will be positively correlated with changes in θ_t^π. When $log(\theta_t^\pi/\theta_{t-1}^\pi)$ is relatively high, $\widehat{g}_t$, overestimates the true growth rate in productivity. Because equipment and human capital are perfect substitutes, investment in equipment will be positively correlated with the production of human capital. In other words, when i_t^e is relatively high, θ_t^π will be relatively low. To test the hypothesis that investment in equipment capital is accompanied by unobservable complementary capital accumulation, I estimate the following equation:

$$\widehat{g}_t = a + \beta_s log(i_t^s/i_{t-1}^s) + \beta_e log(i_t^e/i_{t-1}^e) + w_t \quad (1.43)$$

If labor is being diverted from production towards accumulating human capital when investment in equipment is high, the coefficient β_e should have a negative sign. The same is true for β_s. However, the earlier results indicate that adjustment costs for structures are very small. In that case, we would expect the structures coefficient, β_s, to be zero.

To estimate the growth in productivity in equation (1.41) the total number of labor hours is needed. This is not readily available for the US corporate nonfinancial and NASDAQ sectors. However, the BLS provides these data for the private non-farm business sector and also provides estimates of g using labor and capital inputs (BLS Table XG 4c). Panel A of Table 1.11 reports summary statistics for real annual productivity growth, and real annual structures and equipment investment growth (BEA Fixed Assets Table 4) for the private non-farm business sector from 1949 to 2007. On average, productivity grew at a rate of 1.35% per year during this period.

In real terms, investment in structures capital declined at a rate of 0.06% per year. Real investment in equipment capital grew at rate of 1.22% per year. Productivity growth was much less volatile than investment growth with a standard deviation of 1.82% per year compared to 6.98% for structures and 7.93% for equipment.

Panel B presents OLS regression coefficients, standard errors, t statistics and the R square for the equation (1.43). Consistent with the hypothesis that investment in equipment is accompanied by the diversion of labor towards human capital accumulation, the coefficient estimate for β_e is equal to -10.16% and is statistically significant at the 1% level. Because the dependent and independent variables are in logarithms, this coefficient can be interpreted as an elasticity. Increasing equipment investment growth by 1% leads to a 0.10% decrease in measured productivity. The sign of the coefficient on structures investment growth, β_s, is negative, but is not significantly different from zero. This is consistent with the trivially small indirect adjustment costs estimated in the US corporate nonfinancial and NASDAQ sectors.

1.7 Conclusion

I have shown that a generalized version of the standard neoclassical q-theory model can be used in a valuation context. The prices observed during the late 1990s and early 2000s are roughly consistent with such a model. In standard valuation techniques, subjective forecasts are required to project future cash flows. In the q-theory framework, on the other hand, managers maximize firm value. When firms behave optimally, the shadow price of capital includes a forecast of future marginal cash flows. This price is not directly observable, but it can be inferred – via an adjustment costs function – from a firm's observable investment decisions. When capital is disaggregated into structures and equipment, adjustment costs are not restricted to the quadratic case, such a model does reasonably well at explaining prices of the aggregate US corporate nonfinancial sector. When investment-specific technological change is introduced, the model fits the NASDAQ sector very well. Including first order conditions as moment conditions ensures that managers' forecasts are correct on average – unconditionally, and with respect to the instruments. The implied adjustment costs and shadow prices of capital are reasonably small for the aggregate US market and higher for the NASDAQ sector, but still within the range of past estimates. In this framework, the stock returns predicted by models in both sectors are as volatile as the observed stock returns. I find evidence that supports the idea that investment in equipment is accompanied by unobserved investment in human capital or intangible capital. This diverts labor from production and leads to a decrease in measured productivity.

1.8 Appendix: Detailed Derivations

To derive the relation between stock returns, bond returns and capital investment returns, I roll back the structures and equipment first order conditions one period and multiply by structures and equipment, respectively, use the law of iterated expectations, sum up, and use the linear homogeneity of π, and ϕ to get

$$
\begin{aligned}
&E_t\left[m_{t+\tau-1}\left(q^s_{t+\tau-1}s_{t+\tau}+q^e_{t+\tau-1}e_{t+\tau}\right)\right] \\
&\qquad = E_t\left[m_{t+\tau}\left(\begin{array}{c}
\pi(s_{t+\tau},e_{t+\tau},\theta_{t+\tau})-f_s s_{t+\tau}-f_e e_{t+\tau} \\
-\phi(i^s_{t+\tau},s_{t+\tau},i^e_{t+\tau},e_{t+\tau}) \\
+\phi_{is}(t+\tau)i^s_{t+\tau} \\
+\phi_{ie}(t+\tau)i^e_{t+\tau} \\
+(1-\delta^s_{t+\tau})q^s_{t+\tau}s_{t+\tau} \\
+(1-\delta^e_{t+\tau})q^e_{t+\tau}e_{t+\tau}
\end{array}\right)\right]. \qquad (1.44)
\end{aligned}
$$

Here I have defined $m_{t+\tau}\equiv m_{t,t+\tau}$. Substituting the first order conditions for investment in structures and equipment and using the dynamics of structures and equipment accumulation I get

$$E_t\left[m_{t+\tau-1}\left(q^s_{t+\tau-1}s_{t+\tau}+q^e_{t+\tau-1}e_{t+\tau}\right)\right]$$
$$=E_t\left[m_{t+\tau}\left(\begin{array}{c}\pi(s_{t+\tau},e_{t+\tau},\theta_{t+\tau})-f_s s_{t+\tau}-f_e e_{t+\tau}\\ -\phi(i^s_{t+\tau},s_{t+\tau},i^e_{t+\tau},e_{t+\tau})\\ +q^s_{t+\tau}(i^s_{t+\tau}+s_{t+\tau})\\ +q^e_{t+\tau}(\gamma_{t+\tau}i^e_{t+\tau}+e_{t+\tau})\end{array}\right)\right]. \quad (1.45)$$

Subtracting $E_t[m_{t+\tau}(l_{t+\tau}b_{t+\tau-1}-b_{t+\tau})]$ and $E_t[m_{t+\tau}(q^s_{t+\tau}s_{t+\tau+1}+q^e_{t+\tau}e_{t+\tau+1})]$ from both sides of (1.45) gives us

$$E_t\left[\begin{array}{c}m_{t+\tau-1}\left(q^s_{t+\tau-1}s_{t+\tau}+q^e_{t+\tau-1}e_{t+\tau}\right)\\ -m_{t+\tau}\left(q^s_{t+\tau}s_{t+\tau+1}+q^e_{t+\tau}e_{t+\tau+1}\right)\\ -m_{t+\tau}\left(l_{t+\tau}b_{t+\tau-1}-b_{t+\tau}\right)\end{array}\right]$$
$$=E_t\left[m_{t+\tau}\left(\begin{array}{c}\pi(s_{t+\tau},e_{t+\tau},\theta_{t+\tau})-f_s s_{t+\tau}-f_e e_{t+\tau}\\ -\phi(i^s_{t+\tau},s_{t+\tau},i^e_{t+\tau},e_{t+\tau})\\ +b_{t+\tau}-l_{t+\tau}b_{t+\tau-1}\\ -q^s_{t+\tau}\left(s_{t+\tau+1}-\left(1-\delta^s_{t+\tau}\right)s_{t+\tau}-i^s_{t+\tau}\right)\\ -q^e_{t+\tau}\left(e_{t+\tau+1}-\left(1-\delta^e_{t+\tau}\right)e_{t+\tau}-\gamma_{t+\tau}i^e_{t+\tau}\right)\end{array}\right)\right]. \quad (1.46)$$

Now, notice that the left hand side of (1.46) is equal to the τ^{th} element of the sum in the value function. Applying the fundamental theorem of asset pricing to the firm's debt, we get

$$1=E_t[m_{t+1}l_{t+1}] \quad (1.47)$$

After plugging this in, the right hand side becomes

$$E_t \begin{bmatrix} m_{t+\tau-1}\left(q^s_{t+\tau-1}s_{t+\tau} + q^e_{t+\tau-1}e_{t+\tau} - b_{t+\tau-1}\right) \\ -m_{t+\tau}\left(q^s_{t+\tau}s_{t+\tau+1} + q^e_{t+\tau}e_{t+\tau+1} - b_{t+\tau}\right) \end{bmatrix}. \tag{1.48}$$

The sum of (1.48) from $\tau = 1$ to ∞ combined with the transversality conditions is equal to

$$q^s_t s_{t+1} + q^e_t e_{t+1} - b_t. \tag{1.49}$$

This result combined with the definition value function and the definition of p_t give us the relation:

$$p_t + b_t = q^s_t s_{t+1} + q^e_t e_{t+1}. \tag{1.50}$$

Using the first order conditions (1.8)-(1.11), this can be expressed as:

$$\begin{aligned} p_t + b_t = {} & s_{t+1}E_t\left[m_{t+1}\left(\pi_s(t+1) - f_s - \phi_s(t+1) + (1-\delta^s_{t+1})\phi_{is}(t+1)\right)\right] \\ & + e_{t+1}E_t\left[m_{t+1}\left(\pi_e(t+1) - f_e - \phi_e(t+1) + (1-\delta^e_{t+1})\phi_{ie}(t+1)/\gamma_{t+1}\right)\right]. \end{aligned} \tag{1.51}$$

Define the market leverage ratio, ν_t, as

$$\nu_t \equiv \frac{b_t}{p_t + b_t}. \tag{1.52}$$

Then, using the stock and bond return definition, (1.15), and the bond return identity, $r^B_{t+1} = l_{t+1}$, we get

$$\nu_t r^B_{t+1} + (1-\nu_t) r^S_{t+1} = \frac{\begin{pmatrix} l_{t+1} b_t \\ p_{t+1} + \pi(s_{t+1}, e_{t+1}, \theta_{t+1}) - f_s s_{t+1} - f_e e_{t+1} \\ -\phi(i^s_{t+1}, s_{t+1}, i^e_{t+1}, e_{t+1}) \\ -l_{t+1} b_t + b_{t+1} \end{pmatrix}}{q^s_t s_{t+1} + q^e_t e_{t+1}}. \quad (1.53)$$

Using equation (1.50), the structures and equipment accumulation dynamics yields

$$\nu_t r^B_{t+1} + (1-\nu_t) r^S_{t+1} = \frac{\begin{pmatrix} q^s_{t+1}\left(i^s_{t+1} + \left(1-\delta^s_{t+1}\right) s_{t+1}\right) \\ +q^e_{t+1}\left(\gamma_{t+1} i^e_{t+1} + \left(1-\delta^e_{t+1}\right) e_{t+1}\right) \\ +\pi(s_{t+1}, e_{t+1}, \theta_{t+1}) - f_s s_{t+1} - f_e e_{t+1} \\ -\phi(i^s_{t+1}, s_{t+1}, i^e_{t+1}, e_{t+1}) \end{pmatrix}}{q^s_t s_{t+1} + q^e_t e_{t+1}}. \quad (1.54)$$

Now, plugging in the first order conditions with respect to investment in structures and equipment gives us

$$\nu_t r^B_{t+1} + (1-\nu_t) r^S_{t+1} = \frac{\begin{pmatrix} \pi(s_{t+1}, e_{t+1}, \theta_{t+1}) - f_s s_{t+1} - f_e e_{t+1} \\ +\left(1-\delta^s_{t+1}\right)\phi_{is}(t+1) s_{t+1} \\ +\frac{\left(1-\delta^e_{t+1}\right)\phi_{ie}(t+1)}{\gamma_{t+1}} e_{t+1} \end{pmatrix}}{q^s_t s_{t+1} + q^e_t e_{t+1}}. \quad (1.55)$$

Finally, using the linear homogeneity of π, we get the relation between stock, bond and investment returns:

$$\nu_t r^B_{t+1} + (1-\nu_t) r^S_{t+1} = \omega_t r^I_{st+1} + (1-\omega_t) r^I_{et+1}, \quad (1.56)$$

where ω_t is defined as

$$\omega_t \equiv \frac{q_t^s s_{t+1}}{q_t^s s_{t+1} + q_t^e e_{t+1}}. \tag{1.57}$$

1.9 Appendix: Data

1.9.1 US Corporate Nonfinancial

Investment, Capital, Depreciation and the Price of Investment

I require the quarterly data to conform to the annual data. This is a multi-step procedure. First, I generate quarterly investment and depreciation data for aggregate physical capital that are consistent with the annual data. Next, the quarterly investment data are separated into investment in structures and investment in equipment. Finally, I generate the quarterly structures and quarterly equipment capital stocks using the quarterly investment data and the annual depreciation data.

Total Quarterly Investment and Depreciation

I follow Merz and Yashiv (2005) in constructing the aggregate investment data. First, for the purpose of comparison, I calculate an implied annual investment series for real physical capital using the end-of-year capital stock series from the BEA fixed asset tables 4.1 and 4.2 and the annual depreciation series from BEA fixed asset tables 4.4 and 4.5 according to:

$$i_t = k_t - k_{t-1} + kdepr_t, \tag{1.58}$$

where k_t is the real capital stock (Table 4.1, Item k1nnofi2es000 for the year 2000 multiplied by Table 4.2, series kcnnofi2es000) and $kdepr_t$ is the real capital depreciation (Table 4.4, item m1nnofi2es000 for the year 2000 times Table 4.5 series mcnnofi2es000).

Next, I calculate the real quarterly investment by taking the nominal quarterly investment data from table F.6 of the Flow of Funds Accounts of the Board of Governors of the Federal Reserve (series FA105013005.Q), and deflate them to year 2000 dollars using the nonresidential private fixed investment price index from the BEA's NIPA table 1.1.4 (series B008RG3).

Then, the time-aggregate end of year real investment from the quarterly data (Federal Reserve) is compared to the implied annual real investment from the BEA. Any discrepancy is equally spread between the two series across the quarterly entries of any given year using Denton's (1971) method.

I generate quarterly depreciation rates by dividing the real quarterly consumption of fixed capital (NIPA table 1.14, item N456RX1) by a quarterly log-linear interpolated series using the annual physical capital series from the fixed assets tables 4.1 and 4.2.

Incorporating depreciation, Denton's (1971) method is again used to adjust the quarterly investment series such that annual investment, i_t^e is equal to

$$i_{q,1}(1-\delta_{q,1})(1-\delta_{q,2})(1-\delta_{q,3})+i_{q,2}(1-\delta_{q,2})(1-\delta_{q,3})+i_{q,3}(1-\delta_{q,3})+i_{q,4}, \quad (1.59)$$

where $i_{q,j}$, $j=1,2,3,4$ is equal to investment in quarter j, and $\delta_{q,j}$, $j=1,2,3,4$ is equal to depreciation in quarter j.

Generating Quarterly Structures and Equipment Capital Stock Series

Because I do not have access to quarterly investment data for nonfinancial corporate business broken down by structures and equipment, I assume that the ratio of investment in structures, i_t^s, to equipment, i_t^e, remains constant for the four quarters of each year. If this is the case, the total quarterly investment in capital can be used together with the annual ratio of investment in structures to investment in equipment to generate disaggregated quarterly investment series.

As was done with total investment, I generate implied annual investment in structures and in equipment:

$$i_t^s = s_t - s_{t-1} + depr_t^s \tag{1.60}$$

$$i_t^e = e_t - e_{t-1} + depr_t^e, \tag{1.61}$$

where s_t is the real structures capital stock (Table 4.1, Item k1nnofi2st000 for the year 2000 multiplied by Table 4.2, series kcnnofi2st000), e_t is the real equipment capital stock (Table 4.1, Item k1nnofi2eq000 for the year 2000 multiplied by Table 4.2, series kcnnofi2eq000), $depr_t^s$ is the real structures capital depreciation (Table 4.4, item m1nnofi2st000 for the year 2000 times Table 4.5 series mcnnofi2st000), and $depr_t^e$ is the real equipment capital depreciation (Table 4.4, item m1nnofi2eq000 for the year 2000 times Table 4.5 series mcnnofi2eq000).

Next, the real total quarterly investment is divided into investment in structures and investment in equipment based on to the annual ratio of real investment of the two types of capital.

I generate real quarterly depreciation rates for structures and for equipment by log-linearly interpolating the structures and equipment capital using the annual data from tables 4.1 and 4.2 and then holding constant the annual depreciation rates,

$$\delta_t^s = \frac{depr_t^s}{s_{t-1}} \tag{1.62}$$

$$\delta_t^e = \frac{depr_t^e}{e_{t-1}}, \tag{1.63}$$

through the quarters of year t.

Finally, using starting values, I generate real quarterly capital stock data for structures and equipment according to the capital accumulation equations

$$s_{t+1} = s_t(1 - \delta_t^s) + i_t^s \tag{1.64}$$

$$e_{t+1} = e_t(1 - \delta_t^e) + i_t^e, \tag{1.65}$$

where t now expresses quarters as opposed to years.

1.9.2 NASDAQ data

Output and Total Capital Stock and Investment

From the Compustat quarterly file, I use both sales (data2) as a measure of output, π_t, and Net Property Plant and Equipment (data42) as a measure of total net fixed capital, k_t. Total investment in fixed capital, i_t, is obtained from the Property Plant and Equipment Expenditures series (data90). This item represents the cumulative amount invested over the course of the fiscal year. The appropriate measure for quarters two, three and four is the difference between the current and lagged value. For consistency in aggregation, I require that firms have observations of the variables in the preceding and succeeding quarter.

Structures and Equipment

In Schedule V of the Compustat Industrial Annual file, the stock of firms' PPE is broken down by type. I define structures as the sum of "Buildings", "Construction in Progress", "Natural Resources", "Land and Improvements" and "Capital Leases" and equipment as the sum of "Machinery and Equipment" and "Other"[6]. The categories are reported net of depreciation from 1969 to 1997 and at historical cost from 1984 to 2003. Capital at cost, or gross capital, k_t^g is equal to net capital, k_t, plus accumulated depreciation.

[6] See Tuzel (2007) for a discussion of the categories

Net structures and equipment capital are the variables of interest. However, because Compustat does not disaggregate the annual depreciation expense into these categories it is not possible to calculate these directly using the gross capital data for the latter period. Instead, using data from 1984 to 1993, I regress the ratio s_t/k_t on the ratio k_t^{gs}/k_t^g, and two lags, k_{t-1}^{gs}/k_{t-1}^g and k_{t-2}^{gs}/k_{t-2}^g, and then apply the model out of sample for the years 1994 to 2006. While Compustat reports net capital by type through 1997, the number of firms reporting these items drops significantly starting in 1994. I log-linearly interpolate the annual ratio of (net) structures to total (net) fixed capital to the quarterly frequency and multiply this ratio by the quarterly total fixed capital to generate an approximation of the quarterly structures and equipment capital stocks.

Unfortunately, Compustat also does not report disaggregated investment. In order to estimate both heterogeneous investment and depreciation, I gather annual structures and equipment investment and depreciation data broken down by 63 BEA industry codes from the NIPA Fixed Assets tables. For each of the industries, I calculate the annual ratio of investment in structures to total investment. Next, I match the 4 digit SIC codes from Compustat (dnum) to the BEA industry codes. Assuming that firms in the NASDAQ index behave on average like the average firm in their industries, the value weighted average ratio $i_t^s/(i_t^s + i_t^e)$ will be a good proxy for the true ratio. Depreciation rates, δ_t^s and δ_t, are estimated in a similar manner using capital stocks as weights. Finally, I make the assumption that the annual structures to total investment ratio and the depreciation rates are constant across the quarters of the year. Quarterly investment in structures and equipment is then calculated using the quarterly observations of total investment and the structures to total investment ratios.

Aggregation

Aggregating NASDAQ data in an appropriate manner presents a unique challenge. Ideally, data from every firm listed on the NASDAQ index would be included. In reality, a small percentage of NASDAQ firms (both in terms of numbers and total market size) are *not* included in the Compustat database or are missing data. Figure 1.3 shows the proportion of NASDAQ market capital included in Compustat for four variables. At times, the proportion becomes larger than one. This is because firms' fiscal quarters do not necessarily line up with calendar quarters. I aggregate all available firm data and make the assumption that the aggregate unobserved firms behave as the observed firms on a per-market-capitalization basis.

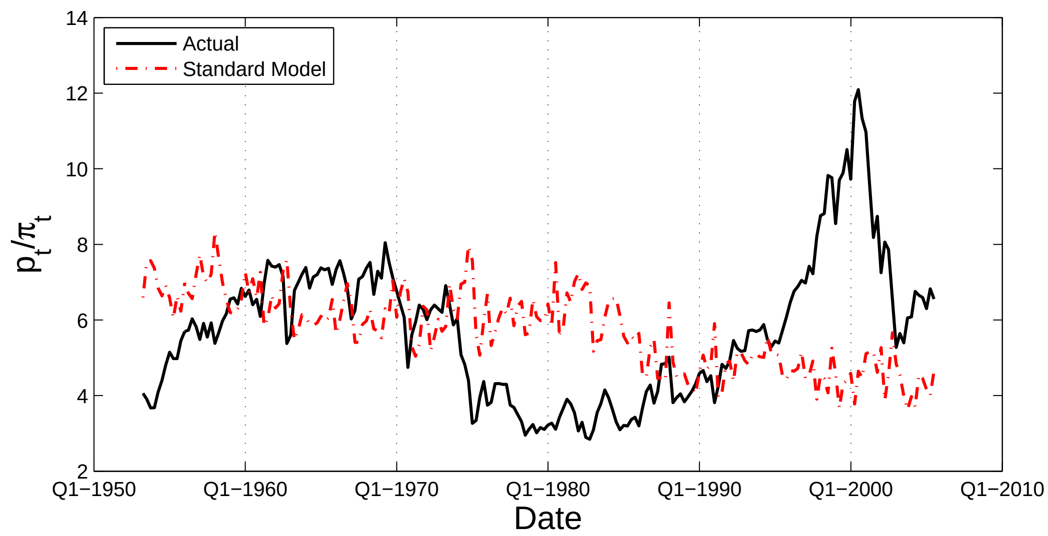
Seasonality

The aggregate US corporate nonfinancial investment data are seasonally adjusted. However, there is seasonality in both the number of NASDAQ firms included in Compustat and the amount of investment. Requiring NASDAQ firms to have observations before and after the current observation corrects for much of the former source. To correct for the latter, I remove seasonal effects using the Census Bureau's X-11 seasonal adjustment procedure. Figure 1.4 compares the adjusted and unadjusted investment series.

Figure 1.1 : Valuation - US Corporate Nonfinancial (1953–2005) and NASDAQ (1983–2005): Standard Model

These panels present actual and predicted market values of equity scaled by total output, p_t/π_t for the US corporate nonfinancial sector (Panel A) from 1953Q1 to 2005Q2 and the NASDAQ sector (Panel B) from 1983Q4 to 2005Q3. For the US corporate nonfinancial sector, The actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real output of nonfinancial corporate business sector from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. For the NASDAQ, the actual values are the market value of equity for all the NASDAQ stocks from CRSP divided by the aggregate sales for all NASDAQ stocks in Compustat adjusted for missing data. The models include quadratic adjustment costs and one capital good and are estimated using Generalized Method of Moments.

Panel A: US Corporate Nonfinancial (1953–2005)



Panel B: NASDAQ (1983–2005)

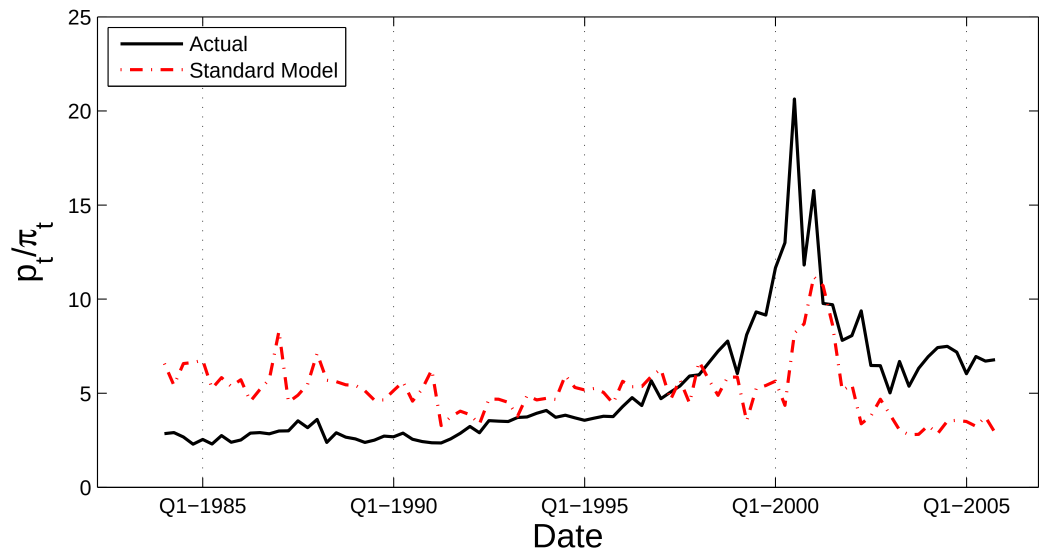
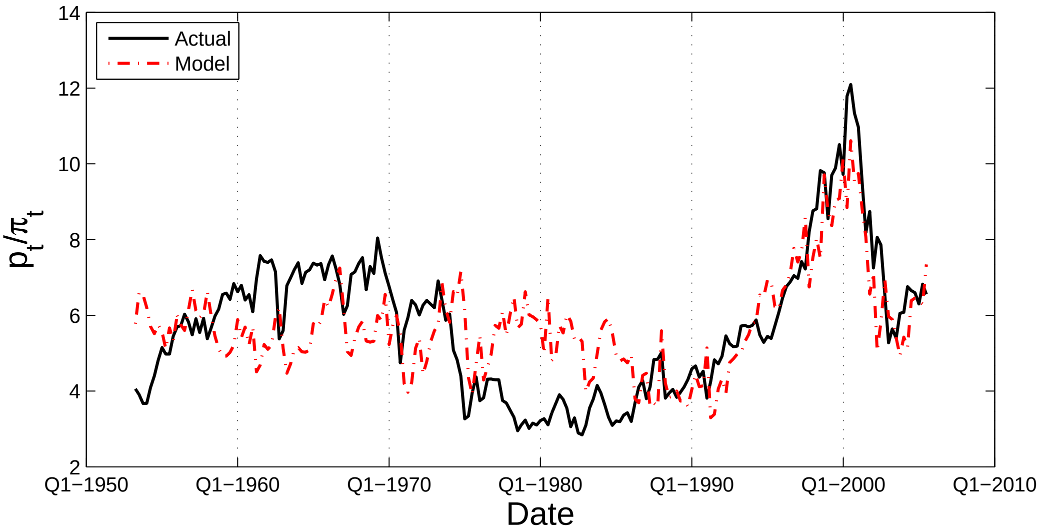


Figure 1.2 : Valuation - US Corporate Nonfinancial (1953–2005) and NASDAQ (1983–2005)

These panels present actual and predicted market values of equity scaled by total output, p_t/π_t for the US corporate nonfinancial sector (Panel A) from 1953Q1 to 2005Q2 and the NASDAQ sector (Panel B) from 1983Q4 to 2005Q3. For the US corporate nonfinancial sector, The actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. For the NASDAQ, the actual values are the market value of equity for all the NASDAQ stocks from CRSP divided by the aggregate sales for all NASDAQ stocks in Compustat adjusted for missing data. The model used in the US corporate nonfinancial series does not include investment specific technological change. Both models are estimated using Generalized Method of Moments.

Panel A: US Corporate Nonfinancial (1953–2005)



Panel B: NASDAQ (1983–2005)

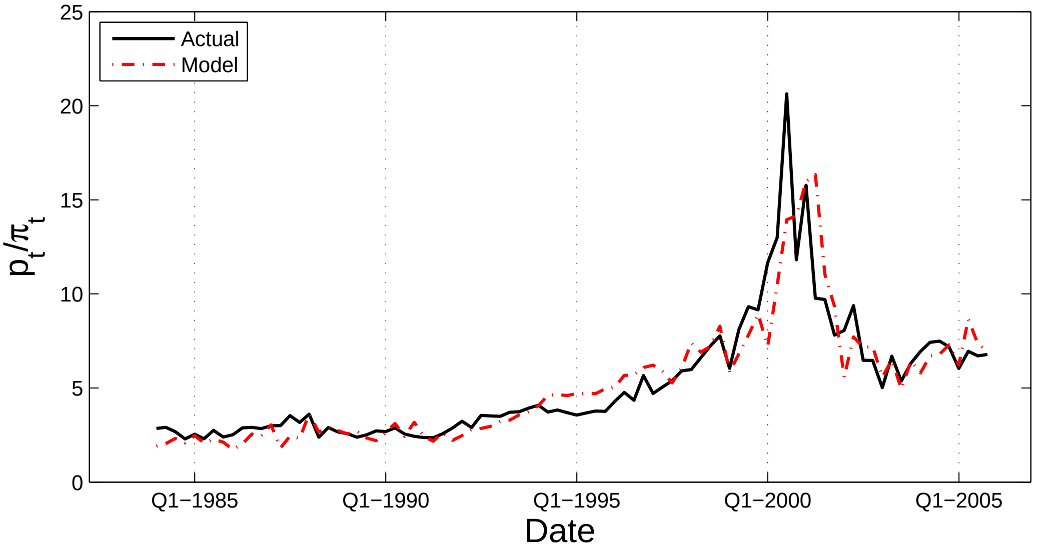


Figure 1.3 : Missing NASDAQ Data in Compustat

This figure presents the total market capitalization from aggregating non-missing data for all NASDAQ firms listed in Compustat as a proportion of the market capitalization of the entire universe of NASDAQ firms. The variables are Sales, π_t, Net Fixed Capital, $(s_t + e_t)$, PPE Expenditures, $(i_t^s + i_t^e)$, and Long Term Debt, b_t.

Proportion of NASDAQ Market Capitalization in Various Compustat Variables

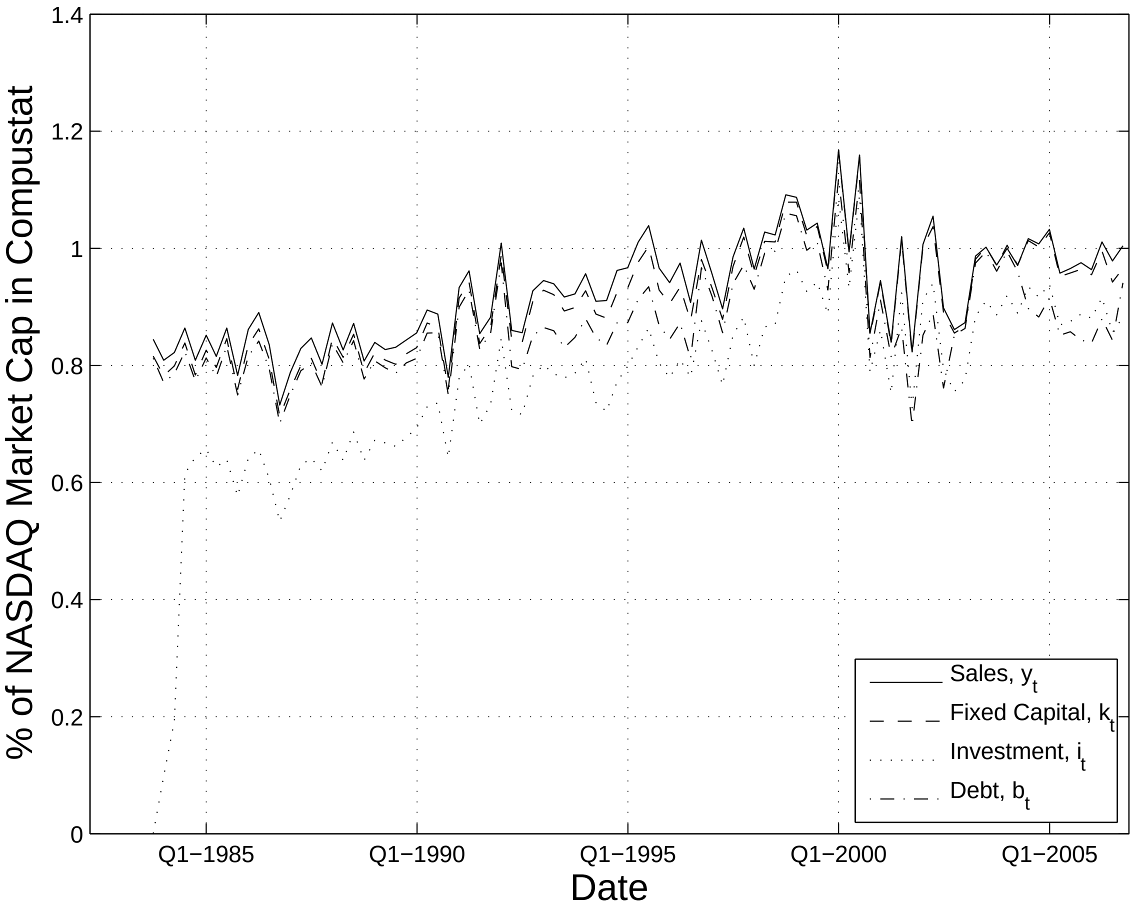


Figure 1.4 : Seasonal Adjustment of NASDAQ Data

This figure presents the aggregate NASDAQ investment-to-capital ratios with and without seasonal adjustment. The Census Bureau's X11 procedure is used to seasonally adjust the data.

NASDAQ Investment Capital Ratios with and without Seasonal Adjustment

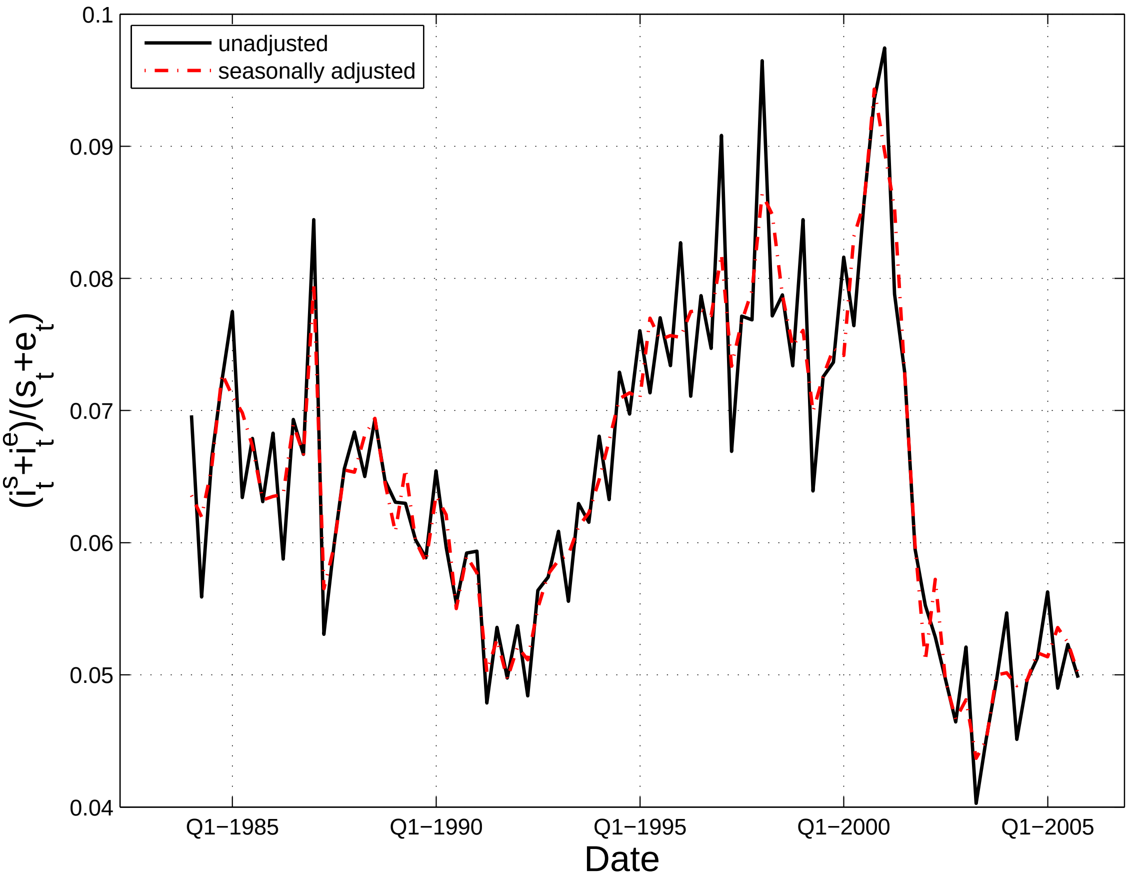
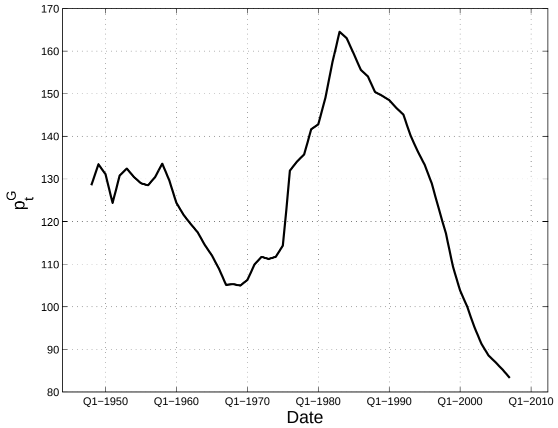


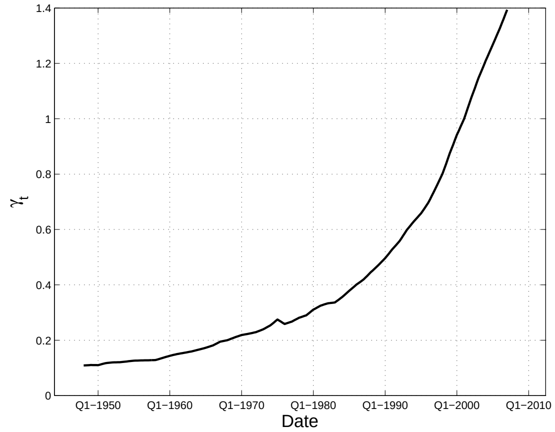
Figure 1.5 : Quality Adjusted Price of Equipment and Software (1947–2006)

Panel A plots the time-series of the quality adjusted price of equipment, p_t^G. Using Gordon's (1990) 22 indexes, the quality bias implicit in the equivalent NIPA price indexes for the 1947-1983 period is calculated and extrapolated using the NIPA data from 1983Q4-2006Q3. The aggregate index is then formed by applying the Tornqvist procedure to the asset-level price indexes. Panel B plots the level of technology in producing equipment capital which is calculated as $\gamma_t = p_t^C / p_t^G$, where p_t^C is a constant-quality price index for consumption constructed by applying the Tornqvist procedure to NIPA data on prices and shares of the consumption of non-durable goods (excluding energy expenditures) and nonhousing services. Panels C and D present the proportion of total capital made up by equipment for the US corporate nonfinancial and NASDAQ sectors with and without investment-specific technological change.

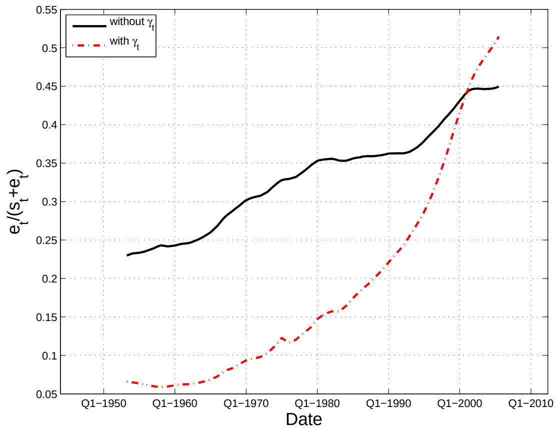
Panel A: Quality Adjusted Price of Equipment, p_t^G



Panel B: Level of Technology for Producing Equipment, γ_t



Panel C: US Corporate Nonfinancial Equipment-to-Total Capital Stock Ratio



Panel D: NASDAQ Equipment-to-Total Capital Stock Ratio

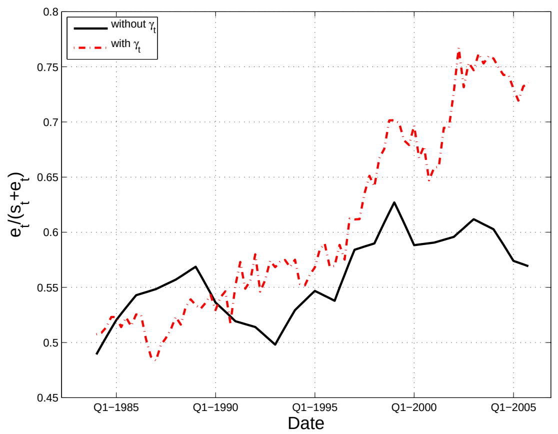
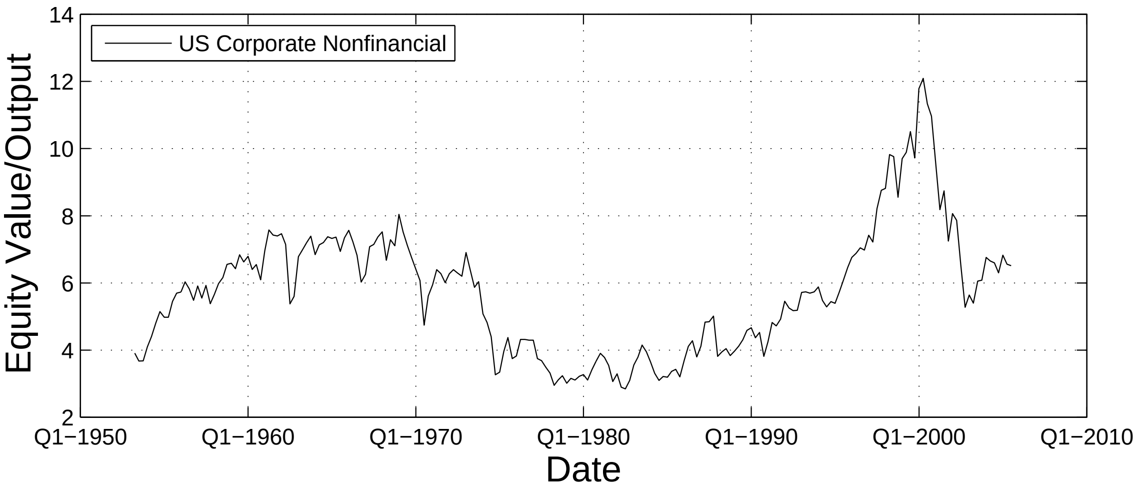


Figure 1.6 : Scaled Market Values of Equity (1953–2005)

These panels present market values of equity scaled by total output, p_t/π_t, for the US corporate nonfinancial sector from 1953Q1 to 2005Q2, and for the NASDAQ sector from 1983Q4 to 2005Q3.For the US Corporate sector, the series is defined as the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. The NASDAQ series is defined as the total market value of equity of all NASDAQ stocks from CRSP divided by the total sales of all NASDAQ stocks adjusted for missing data. Data are quarterly.

Panel A: US Corporate Nonfinancial (1953-2005)



Panel B: US Corporate Nonfinancial and NASDAQ (1983-2005)

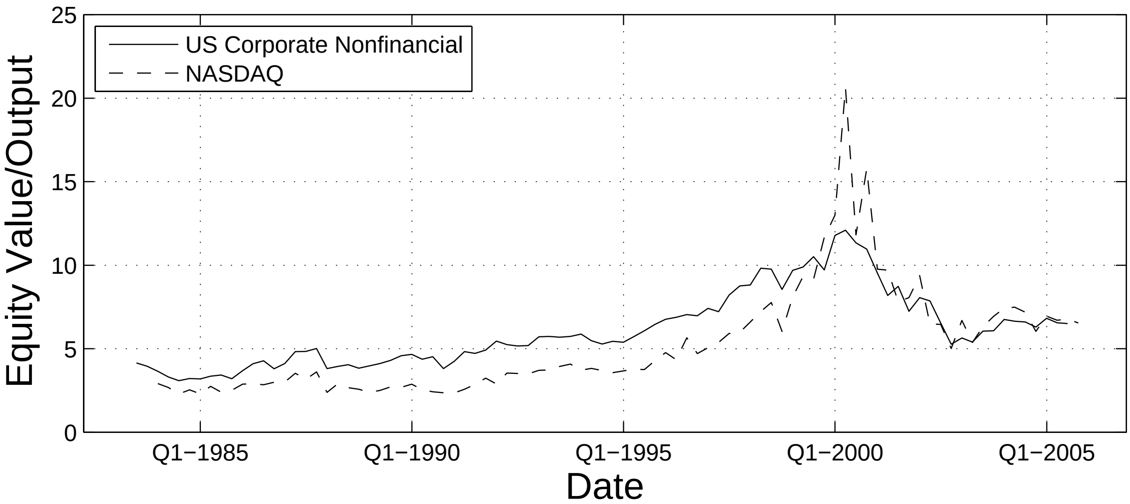
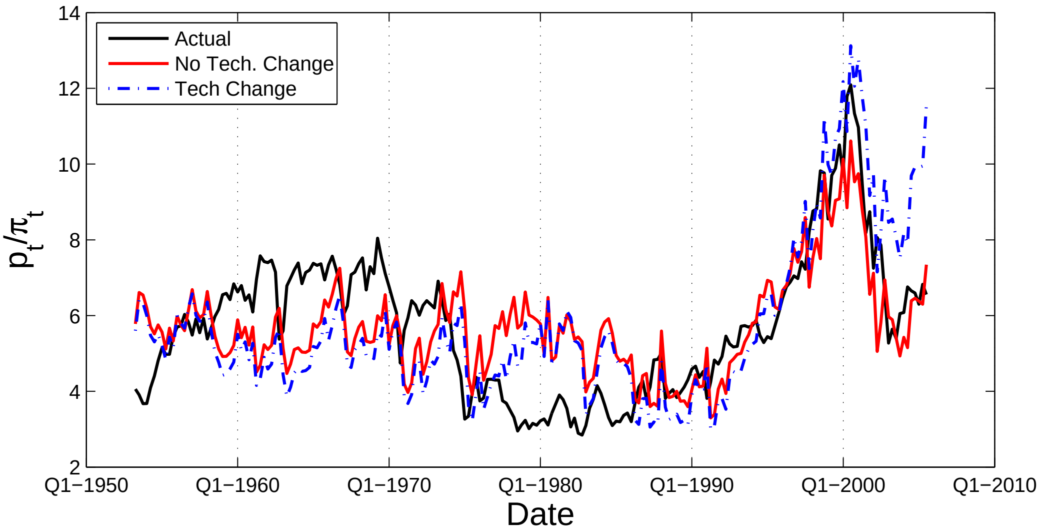


Figure 1.7 : Valuation - US Corporate Nonfinancial (1953–2005) and NASDAQ (1983–2005)

These panels present actual and predicted market values of equity scaled by total output, p_t/π_t for the US corporate nonfinancial sector (Panel A) from 1953Q1 to 2005Q2 and the NASDAQ sector (Panel B) from 1983Q4 to 2005Q3. For the US corporate nonfinancial sector, The actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. For the NASDAQ, the actual values are the market value of equity for all the NASDAQ stocks from CRSP divided by the aggregate sales for all NASDAQ stocks in Compustat adjusted for missing data. The other two series are those generated by the generalized model with and without ($\gamma_t = 1$) investment-specific technological change.

Panel A: US Corporate Nonfinancial (1953–2005)



Panel B: NASDAQ (1983–2005)

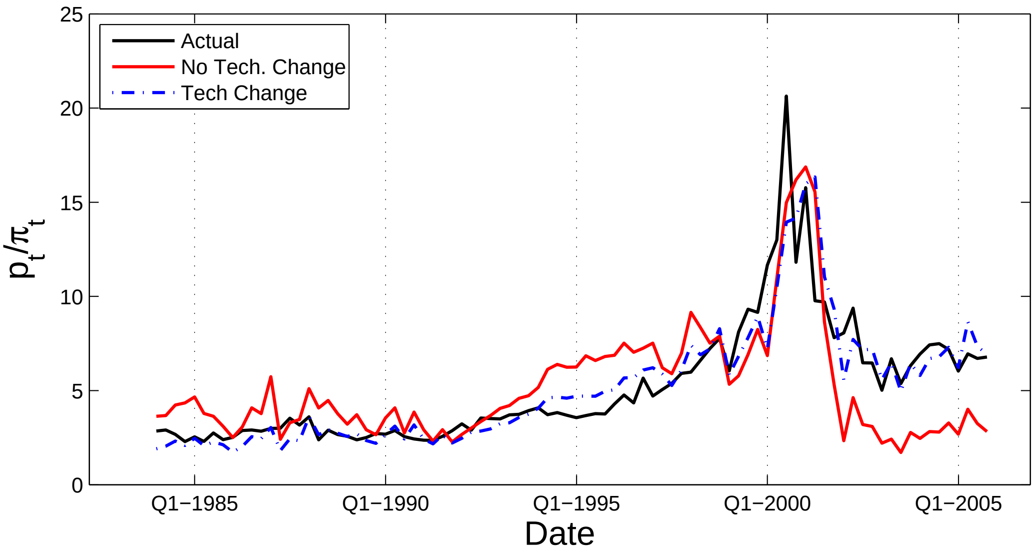
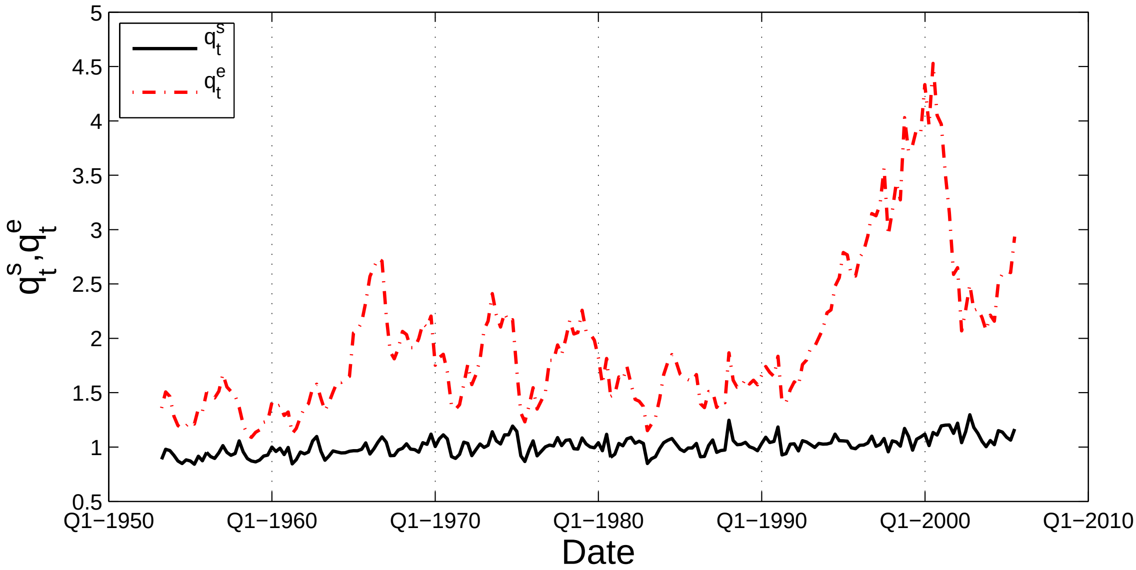


Figure 1.8 : Marginal Adjustment Costs

These panels present the implied marginal adjustment costs, q_t^s and q_t^e for the US corporate nonfinancial sector from 1953Q1 to 2005Q2, and for the NASDAQ sector from 1983Q4 to 2005Q3. The adjustment costs for the US corporate nonfinancial sector (Panel A) are those implied by the model without investment-specific technological change in the first column of Table 1.2. The implied adjustment costs in the NASDAQ sector are those from the model with investment-specific technological change in the final column of Table 1.2. Data are quarterly.

Panel A: US Corporate Nonfinancial (1953-2005)



Panel B: NASDAQ (1983-2005)

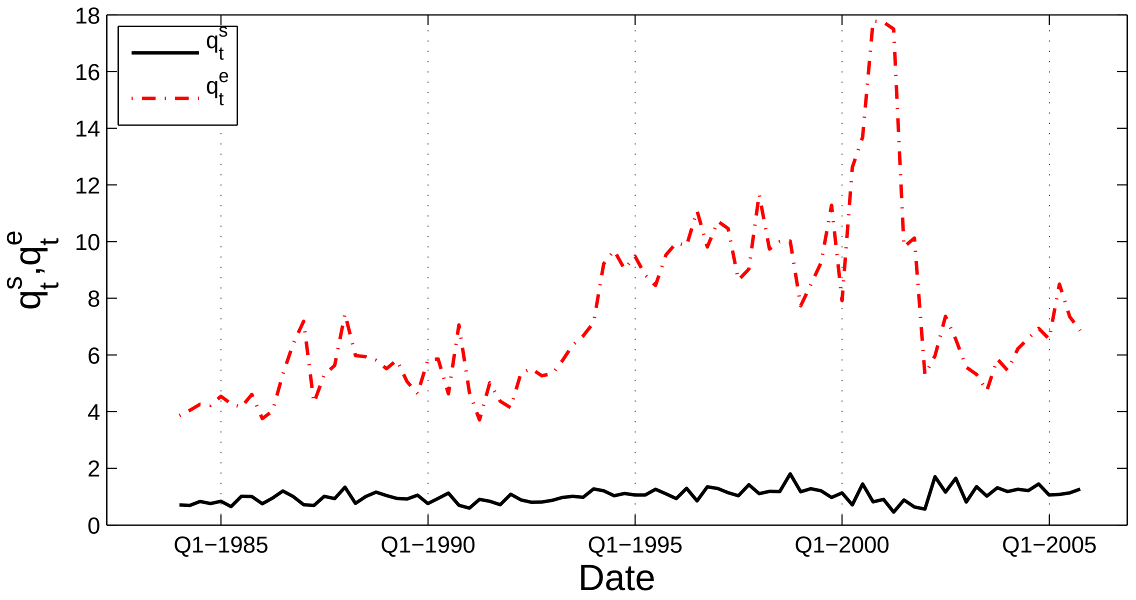
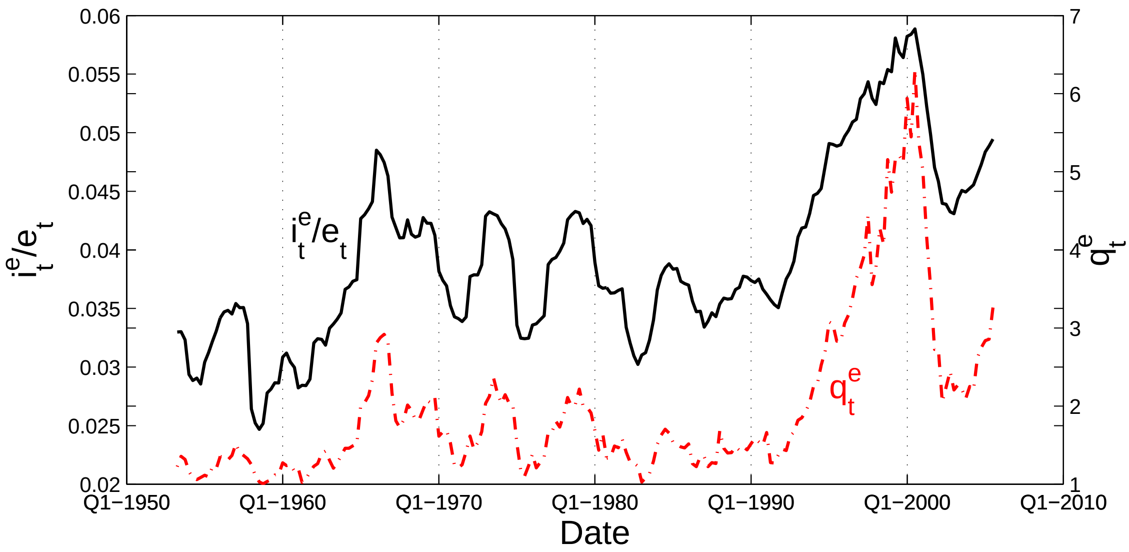


Figure 1.9 : Marginal Adjustment Costs and Investment Capital Ratios

These panels present the implied marginal adjustment costs for equipment and the equipment investment-capital ratios for the US corporate nonfinancial sector from 1953Q1 to 2005Q2, and for the NASDAQ sector from 1983Q4 to 2005Q3. The adjustment costs, q_t^e, and investment-capital ratio, i_t^e/e_t, for the US corporate nonfinancial sector (Panel A) are those implied by the model without investment-specific technological change in the first column of Table 1.2. The implied adjustment costs, $_t$, and investment-capital ratio, $i^e\gamma_t/e_t^\gamma$ in the NASDAQ sector are those from the model with investment-specific technological change in the final column of Table 1.2. Data are quarterly.

Panel A: US Corporate Nonfinancial (1953-2005)



Panel B: NASDAQ (1983-2005)

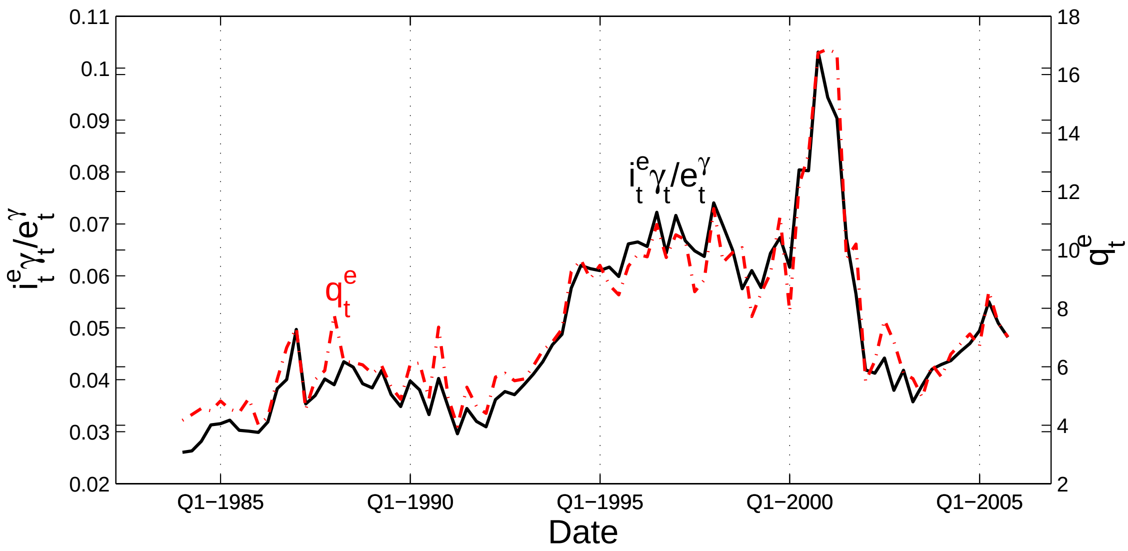
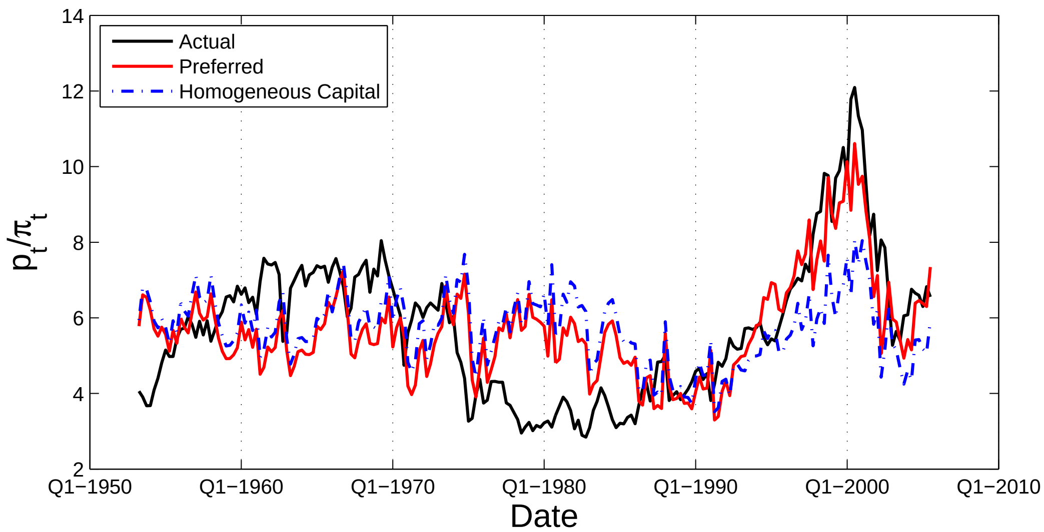


Figure 1.10 : Valuation - Homogeneous Capital

These two panels present actual and predicted market values of equity scaled by total output, p_t/π_t, assuming that capital is homogeneous. Panel A presents results for the US corporate nonfinancial sector from 1953Q1 to 2005Q2, and Panel B presents results for the NASDAQ sector from 1983Q4 to 2005Q3. For the US Corporate sector, the actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. The preferred series in Panel A is from the generalized model with no investment-specific technological change ($\gamma_t = 1$). For the NASDAQ, the actual values are the market value of equity for all the NASDAQ stocks from CRSP divided by the aggregate sales for all NASDAQ stocks in Compustat adjusted for missing data. The preferred series in Panel B is from the generalized model with investment-specific technological change.

Panel A: US Corporate Nonfinancial



Panel B: NASDAQ

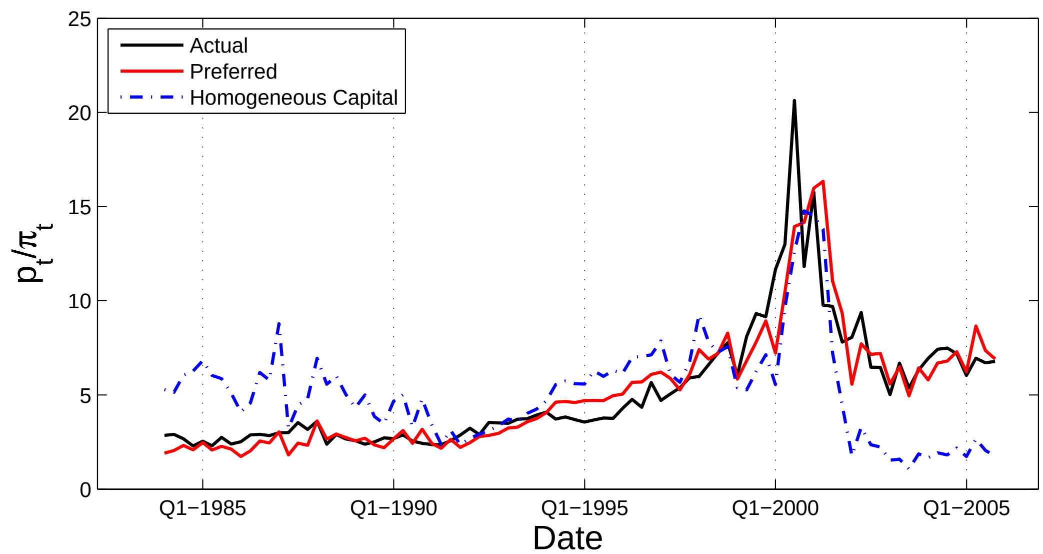
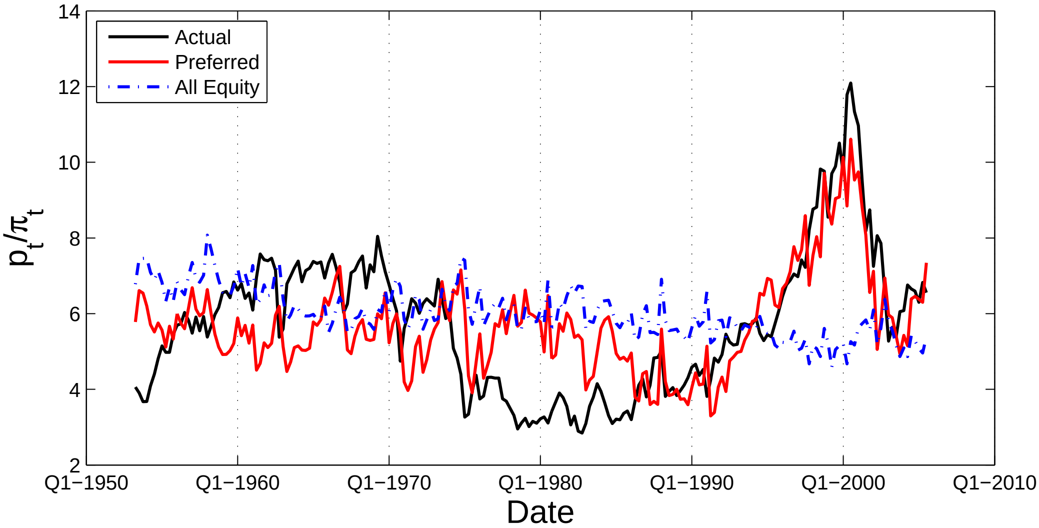


Figure 1.11 : Valuation - All Equity Model

These two panels present actual and predicted market values of equity scaled by total output, p_t/π_t, assuming that firms are entirely equity financed. Panel A presents results for the US corporate nonfinancial sector from 1953Q1 to 2005Q2, and Panel B presents results for the NASDAQ sector from 1983Q4 to 2005Q3. For the US Corporate sector, the actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. The preferred series in Panel A is from the generalized model with no investment-specific technological change ($\gamma_t = 1$). For the NASDAQ, the actual values are the market value of equity for all the NASDAQ stocks from CRSP divided by the aggregate sales for all NASDAQ stocks in Compustat adjusted for missing data. The preferred series in Panel B is from the generalized model with investment-specific technological change.

Panel A: US Corporate Nonfinancial



Panel B: NASDAQ

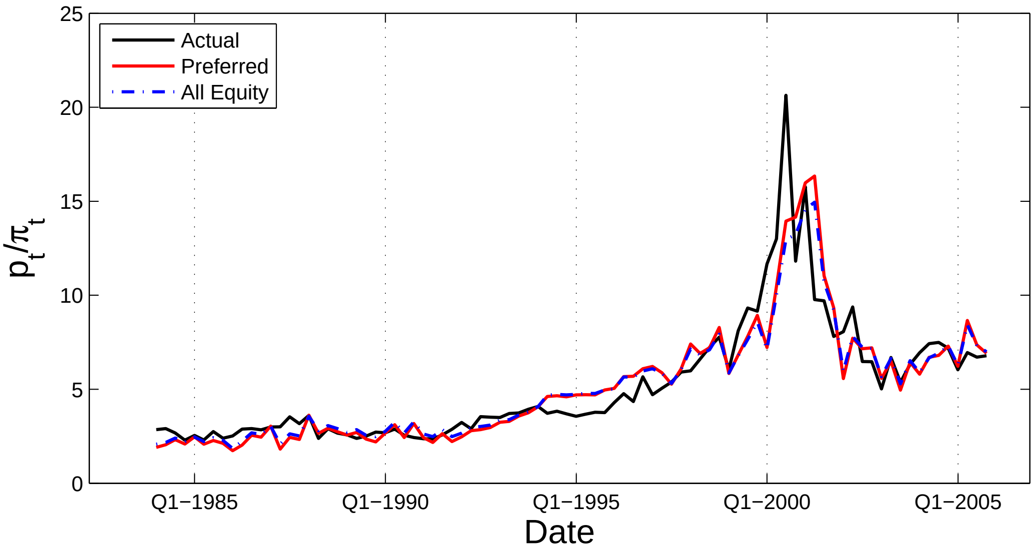
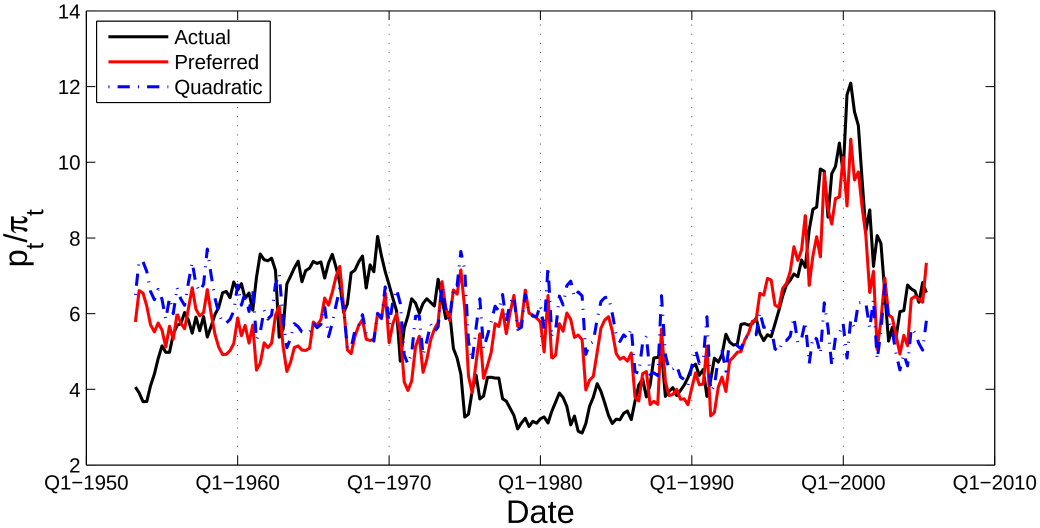


Figure 1.12 : Valuation - Quadratic Adjustment Costs

These two panels present actual and predicted market values of equity scaled by total output, p_t/π_t, assuming that adjustment costs functions are quadratic. Panel A presents results for the US corporate nonfinancial sector from 1953Q1 to 2005Q2, and Panel B presents results for the NASDAQ sector from 1983Q4 to 2005Q3. For the US Corporate sector, the actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. The preferred series in Panel A is from the generalized model with no investment-specific technological change ($\gamma_t = 1$). For the NASDAQ, the actual values are the market value of equity for all the NASDAQ stocks from CRSP divided by the aggregate sales for all NASDAQ stocks in Compustat adjusted for missing data. The preferred series in Panel B is from the generalized model with investment-specific technological change.

Panel A: US Corporate Nonfinancial



Panel B: NASDAQ

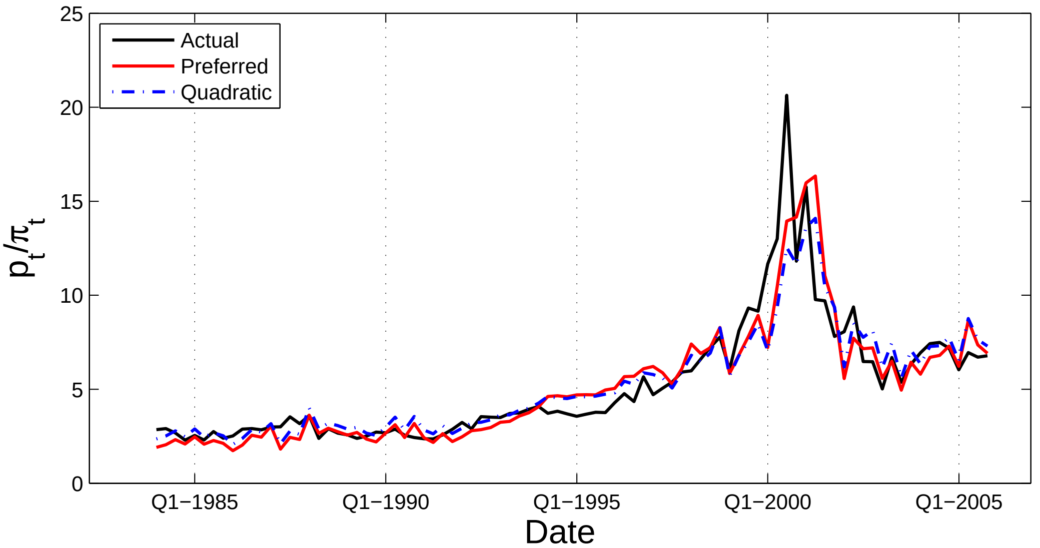
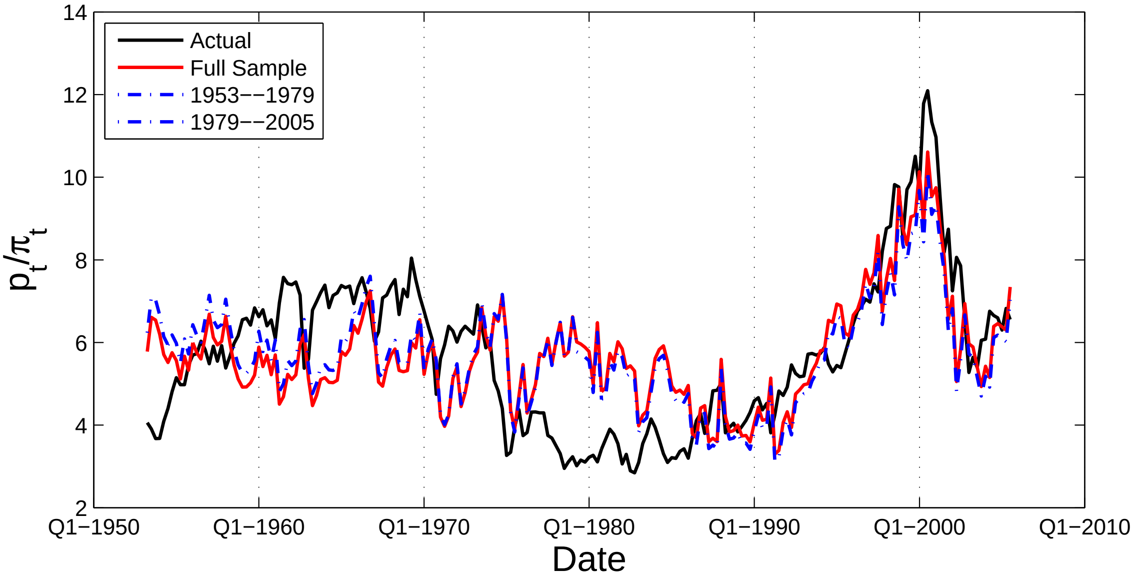


Figure 1.13 : Valuation - US Corporate Nonfinancial - Subsample Analysis

These panels present actual and predicted market values of equity scaled by total output, p_t/π_t. The actual values are from the market value of shares outstanding for nonfinancial corporate business from the Federal Reserve (Table B.102, series FL103164003.Q) divided by the real gross value added of nonfinancial corporate business from Table 1.14 (series A457RX1) of the NIPA accounts published by the BEA of the Department of Commerce. The other three series are those generated by the generalized model for the entire sample, from 1953Q1 to 1979Q1, and 1979Q2 to 2005Q2l. Panel A presents the series with no investment-specific technological change. Panel B presents the results with investment-specific technological change.

Panel A: No Investment-Specific Technological Change



Panel B: Investment-Specific Technological Change

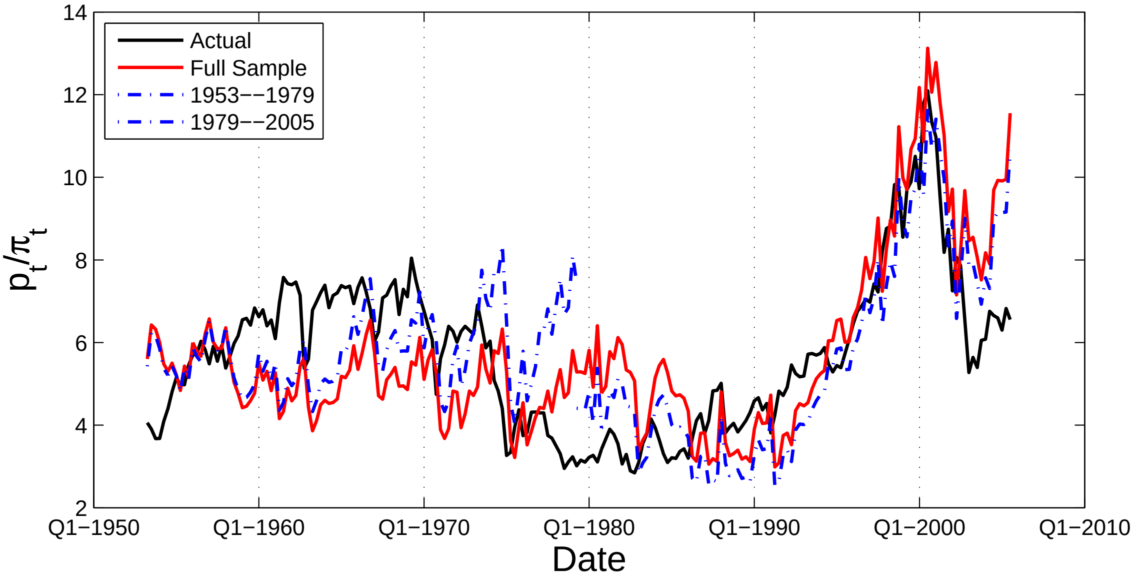
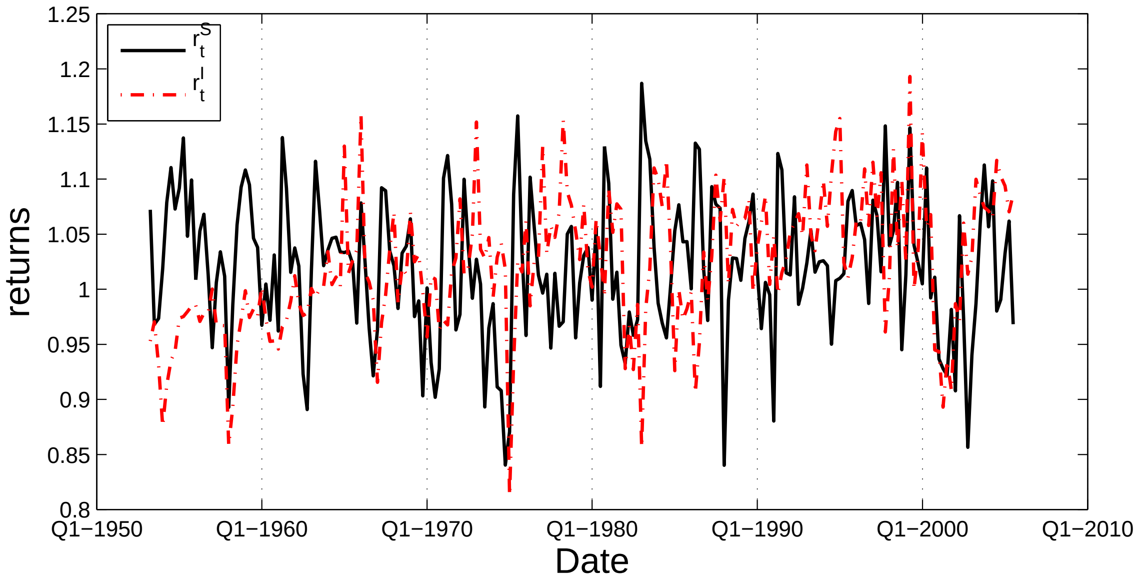


Figure 1.14 : Stock Returns

These panels present actual and predicted stock returns for the US corporate nonfinancial sector and the NASDAQ sector. Panel A presents the results for the US corporate nonfinancial sector using the model with leverage and without investment-specific technological change in Table 1.2 for the period 1953Q1–2005Q2. Panel B presents the results for the NASDAQ sector using the model with leverage and with investment specific technological change in Table 1.2. The stock returns are from the CRSP value weighted portfolio in Panel A, and the NASDAQ value weighted index from CRSP in Panel B. Both are deflated using the CPI.

Panel A: US Corporate Nonfinancial



Panel B: NASDAQ

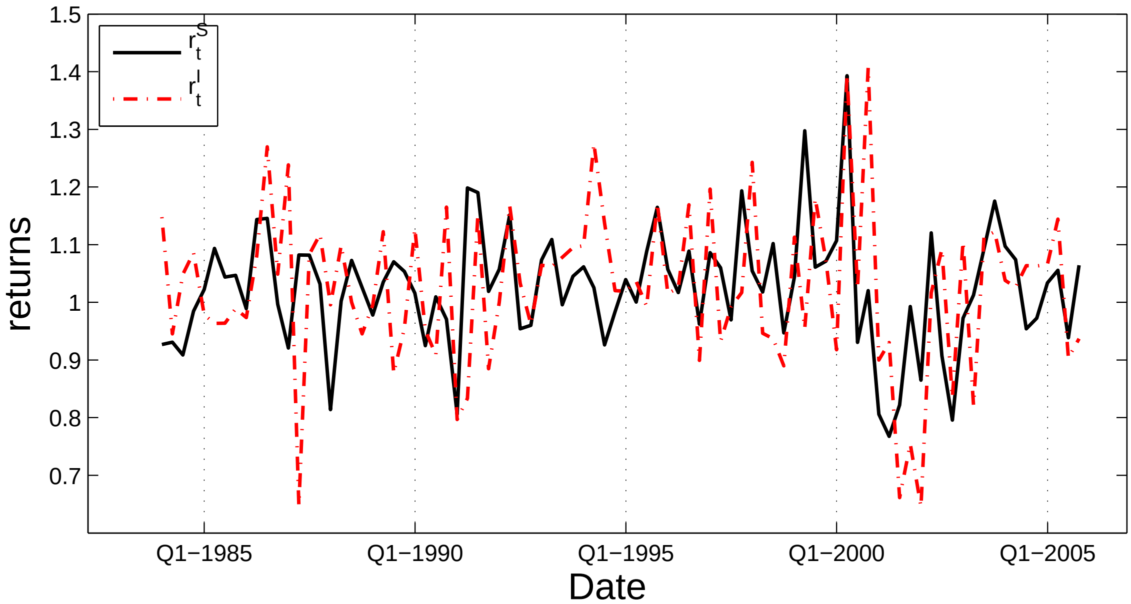


Table 1.1 : Descriptive Statistics for the US Corporate Nonfinancial (1953–2005) and NASDAQ (1983–2005) sectors

This table reports sample averages, standard deviations, minima, and maxima of data for the US corporate nonfinancial and NASDAQ sectors. The variables consist of the structures investment-capital ratio, i_t^s/s_t, equipment investment-capital ratios, i_t^e/e_t & $i_t^e\gamma_t/k_t^{e\gamma}$, equipment capital shares, $e_t/(s_t+e_t)$ & $e_t^{\gamma}/(s_t+e_t^{\gamma})$, depreciation rates, δ_t^s, δ_t^e, & $\delta_t^{e\gamma}$, leverage ratios, $b_t/(t_t+b_t)$, scaled market values of equity, p_t/π_t, and gross stock and bond returns, r_t^s & r_b^s. The output variables are gross value added for the US and sales for the NASDAQ sector. US data come from the BEA, Federal Reserve and CRSP and cover the period from 1953Q1–2005Q2. The NASDAQ data are from Compustat, CRSP and the BEA and cover the period from 1983Q4–2005Q3. The timing of the stock and bond returns has been adjusted to match the macroeconomic data as in Cochrane (1996).

	Panel A: US Corporate				Panel B: NASDAQ			
	Mean	St Dev	Max	Min	Mean	St Dev	Max	Min
i_t^s/s_t	1.32%	0.18%	1.68%	1.01%	3.67%	1.31%	6.53%	1.33%
i_t^e/e_t	3.94%	0.75%	5.89%	2.47%	8.70%	1.64%	13.34%	6.31%
$i_t^e\gamma_t/e_t^{\gamma}$	3.66%	1.06%	5.97%	1.58%	4.91%	1.65%	10.31%	2.60%
$e_t/(s_t+e_t)$	33.25%	6.52%	44.96%	22.99%	55.93%	3.52%	62.70%	48.92%
$e_t^{\gamma}/(s_t+e_t^{\gamma})$	18.53%	13.29%	51.46%	5.86%	60.78%	8.66%	76.73%	48.36%
δ_t^s	0.73%	0.03%	0.80%	0.68%	0.72%	0.02%	0.77%	0.69%
δ_t^e	2.87%	0.61%	4.27%	2.24%	4.23%	0.57%	5.20%	3.42%
$\delta_t^{e\gamma}$	3.96%	1.02%	5.85%	1.03%	5.66%	0.68%	6.85%	4.64%
$b_t/(p_t+b_t)$	35.3%	7.7%	50.3%	21.5%	17.1%	3.3%	26.6%	7.6%
p_t/π_t	5.73	1.87	12.09	2.84	5.21	3.21	20.63	2.29
r_t^s	1.02	0.06	1.19	0.84	1.02	0.10	1.39	0.77
r_t^b	1.01	0.04	1.20	0.88	1.02	0.03	1.11	0.93

Table 1.2 : GMM Estimation Results for the US Corporate Nonfinancial and NASDAQ sectors.

This table reports parameter estimates, standard errors, J_T statistics and p-values for the US corporate nonfinancial sector from a GMM estimation procedure. The parameter α represents the structures output elasticity. The parameters e_s and e_e control scale in the adjustment cost function, while η_s and η_e are power parameters. The flow operating cost parameters are f_s and f_e. Four moments and five instruments are used in the estimation. The four moments are the first order conditions (1.20) and (1.21), the valuation function (1.22), and the stock-investment returns relation (1.23). The US corporate nonfinancial data are quarterly and cover the period from 1953Q1–2005Q. The NASDAQ data are quarterly and cover the period from 1983Q4–2005Q3. Five instrumental variables are also included. Corporate bond data are from Ibbotson's index of Long Term Corporate bonds. The default premium, def_t, is defined as the difference between the yields of Aaa and Baa corporate bonds. The term premium, $term_t$, is the yield on ten-year notes minus that on three-month Treasury bills. The risk free rate, rf_t, is from Ken French's website. The equally weighted aggregate dividend yield, div_t, is from CRSP. Finally, I use the Lettau and Ludvigsen consumption-to-wealth ratio, cay_t.The timing of the stock and bond returns has been adjusted to match the macroeconomic data as in Cochrane (1996). Two stage GMM is used with an identity weighting matrix in the first stage and an optimal weighting matrix in the second stage. Six Newey-West lags are used to estimate the optimal weighting matrix. In three cases, the structures adjustment costs coefficient, a_s is set to zero. Standard errors are in parentheses.

	Panel A: US Corporate Nonfin.			Panel B: NASDAQ			
	No Tech. Change		Tech. Change	No Tech. Change		Tech. Change	
restr.:	none	($a_s = 0$)	none	none	($a_s = 0$)	none	($a_s = 0$)
α	0.95	0.92	0.95	0.86	0.98	0.96	0.95
	(0.14)	(0.13)	(0.02)	(0.13)	(0.13)	(0.08)	(0.08)
a_s	0.04		7.30	5.71		7.85	
	(1.57)		(3.36)	(66.14)		(18.50)	
a_e	10.60	10.37	9.86	7.32	7.29	8.34	8.35
	(0.63)	(0.41)	(0.73)	(0.10)	(0.08)	(0.11)	(0.10)
η_s	1.43		2.67	6.64		8.98	
	(2.99)		(0.64)	(88.55)		(32.38)	
η_e	6.54	6.04	5.45	3.68	3.57	2.18	2.19
	(0.92)	(0.47)	(0.90)	(0.30)	(0.19)	(0.06)	(0.05)
f_s	0.19	0.19	0.20	1.94	2.25	2.19	2.14
	(0.03)	(0.03)	(0.01)	(0.31)	(0.30)	(0.19)	(0.18)
f_e	-0.02	-0.01	0.02	0.18	-0.07	-0.21	-0.07
	(0.06)	(0.06)	(0.02)	(0.26)	(0.26)	(0.13)	(0.13)
TJ_T	23.93	25.64	21.99	12.13	12.13	10.87	10.95
p-value	0.121	0.140	0.170	0.792	0.880	0.863	0.926

Table 1.3 : Adjustment Costs

This table reports time series means and standard deviations for total adjustment as a proportion of output, $(\phi_t - i_t^s - i^e)/\pi_t$, structures investment relative to output, i_t^s/π_t, equipment investment relative to output, i_t^e/π_t the shadow price of structures, q_t^s, and the shadow price of capital, q_t^e for the US corporate nonfinancial and NASDAQ sectors using 6 models. Panel A presents the results for the US corporate nonfinancial sector from 1953Q1–2005Q2. Panel B presents results for the NASDAQ sector from 1983Q4–2005Q3. Standard deviations are in parentheses.

Panel A: US Corporate Nonfinancial

	Without Tech. Change	With Tech. Change
	Leverage	Leverage
$(\phi_t - i_t^s - i^e)/\pi_t$	0.020	0.025
	(0.021)	(0.029)
i_t^s/π_t	0.059	0.059
	(0.014)	(0.014)
i^e/π_t	0.084	0.084
	(0.021)	(0.021)
q_t^s	1.000	1.364
	(0.000)	(0.159)
q_t^e	1.954	2.199
	(0.703)	(0.885)

Panel B: NASDAQ

	Without Tech. Change		With Tech. Change	
	All-Equity	Leverage	All-Equity	Leverage
$(\phi_t - i_t^s - i_t^e)/\pi_t$	0.103	0.138	0.096	0.123
	(0.093)	(0.115)	(0.100)	(0.125)
i_t^s/π_t	0.017	0.017	0.017	0.017
	(0.007)	(0.007)	(0.007)	(0.007)
i_t^e/π_t	0.049	0.049	0.049	0.049
	(0.014)	(0.014)	(0.014)	(0.014)
q_t^s	1.022	1.000	1.024	1.000
	(0.269)	(0.000)	(0.251)	(0.000)
q_t^e	8.050	9.789	6.045	7.331
	(4.142)	(4.587)	(2.533)	(3.031)

Table 1.4 : GMM Estimation Results for the US Corporate Nonfinancial and NASDAQ sectors using homogeneous capital

This table reports parameter estimates, standard errors, J_T statistics and p-values for the US corporate nonfinancial and NASDAQ sectors from a GMM estimation procedure. The parameter a control scale in the adjustment cost function, while η is the power parameter. The flow operating cost parameter is f. Three moments and five instruments are used in the estimation. The three moments are the first order conditions for investment in capital, the valuation function, and the stock-investment returns relation. The US corporate nonfinancial data are quarterly and cover the period from 1953Q1–2005Q2. The NASDAQ data are quarterly and cover the period from 1983Q4–2005Q3. Five instrumental variables are also included. Corporate bond data are from Ibbotson's index of Long Term Corporate bonds. The default premium, def_t, is defined as the difference between the yields of Baa and Aaa corporate bonds. The term premium, $term_t$, is the yield on ten-year notes minus that on three-month Treasury bills. The risk free rate, rf_t, is from Ken French's website. The equally weighted aggregate dividend yield, div_t, is from CRSP. Finally, I use the Lettau and Ludvigsen consumption-to-wealth ratio, cay_t. The timing of the stock and bond returns has been adjusted to match the macroeconomic data as in Cochrane (1996). Two stage GMM is used with an identity weighting matrix in the first stage and an optimal weighting matrix in the second stage. Six Newey-West lags are used to estimate the optimal weighting matrix. In three cases, the structures adjustment costs coefficient, a_s is set to zero. Time series standard deviations are in parentheses.

	Panel A: US Corporate Nonfinancial	Panel B: NASDAQ	
	Leverage	All Equity	Leverage
a	16.71	7.43	7.69
	(0.96)	(0.25)	(0.25)
η	7.14	2.76	2.54
	(0.61)	(0.17)	(0.16)
f	0.12	0.83	0.81
	(0.01)	(0.05)	(0.06)
TJ_T	19.11	11.39	11.27
p-value	0.209	0.724	0.733

Table 1.5 : GMM Estimation Results for the US Corporate Nonfinancial and NASDAQ Sectors - Alternate Specifications.

This table reports parameter estimates, standard errors, J_T statistics and p-values for the US corporate nonfinancial sector from a GMM estimation procedure. The parameter α represents the structures output elasticity. The parameters e_s and e_e control scale in the adjustment cost function, while η_s and η_e are power parameters. The flow operating cost parameters are f_s and f_e. Four moments and five instruments are used in the estimation. The four moments are the first order conditions (1.20) and (1.21), the valuation function (1.22), and the stock-investment returns relation (1.23). The US corporate nonfinancial data are quarterly and cover the period from 1953Q1–2005Q2. The NASDAQ data are quarterly and cover the period from 1983Q4–2005Q3. Five instrumental variables are also included. Corporate bond data are from Ibbotson's index of Long Term Corporate bonds. The default premium, def_t, is defined as the difference between the yields of Aaa and Baa corporate bonds. The term premium, $term_t$, is the yield on ten-year notes minus that on three-month Treasury bills. The risk free rate, rf_t, is from Ken French's website. The equally weighted aggregate dividend yield, div_t, is from CRSP. Finally, I use the Lettau and Ludvigsen consumption-to-wealth ratio, cay_t.The timing of the stock and bond returns has been adjusted to match the macroeconomic data as in Cochrane (1996). Two stage GMM is used with an identity weighting matrix in the first stage and an optimal weighting matrix in the second stage. Six Newey-West lags are used to estimate the optimal weighting matrix. In three cases, the structures adjustment costs coefficient, a_s is set to zero. Standard errors are in parentheses.

	Panel A: US Corporate Nonfin.	Panel B: NASDAQ		
	Quadratic	All Equity		Quadratic
restrictions:	($\eta_s = \eta_e = 2$)		($a_s = 0$)	($\eta_s = \eta_e = 2$)
α	0.96	0.97	0.96	0.90
	(0.10)	(0.08)	(0.07)	(0.07)
a_s	1.18	7.66		1.10
	(1.04)	(23.38)		(1.09)
a_e	3.43	7.84	7.89	8.04
	(0.22)	(0.11)	(0.11)	(0.09)
η_s		8.98		
		(40.66)		
η_e		2.40	2.43	
		(0.07)	(0.06)	
f_s	0.19	2.19	2.16	2.02
	(0.02)	(0.17)	(0.16)	(0.16)
f_e	-0.04	-0.16	-0.05	-0.11
	(0.04)	(0.12)	(0.11)	(0.11)
TJ_T	25.99	11.05	11.08	11.22
p-value	0.130	0.854	0.921	0.916

Table 1.6 : GMM Estimation Results for the US Corporate Nonfinancial Sector - Subsample Analysis.

This table reports parameter estimates, standard errors, J_T statistics and p-values for the US corporate nonfinancial sector from a GMM estimation procedure. The parameter α represents the structures output elasticity. The parameters e_s and e_e control scale in the adjustment cost function, while η_s and η_e are power parameters. The flow operating cost parameters are f_s and f_e. Four moments and five instruments are used in the estimation. The four moments are the first order conditions (1.20) and (1.21), the valuation function (1.22), and the stock-investment returns relation (1.23). The US corporate nonfinancial data are quarterly and cover the period from 1953Q1–1979Q1 . Five instrumental variables are also included. Corporate bond data are from Ibbotson's index of Long Term Corporate bonds. The default premium, def_t, is defined as the difference between the yields of Aaa and Baa corporate bonds. The term premium, $term_t$, is the yield on ten-year notes minus that on three-month Treasury bills. The risk free rate, rf_t, is from Ken French's website. The equally weighted aggregate dividend yield, div_t, is from CRSP. Finally, I use the Lettau and Ludvigsen consumption-to-wealth ratio, cay_t.The timing of the stock and bond returns has been adjusted to match the macroeconomic data as in Cochrane (1996). Two stage GMM is used with an identity weighting matrix in the first stage and an optimal weighting matrix in the second stage. Six Newey-West lags are used to estimate the optimal weighting matrix. In three cases, the structures adjustment costs coefficient, a_s is set to zero. Standard errors are in parentheses.

	Panel A: 1953Q1–1979Q1		Panel B: 1979Q2–2005Q2	
	No Tech. Change ($\gamma_t = 1$)	Tech. Change	No Tech. Change ($\gamma_t = 1$)	Tech. Change
α	0.32	0.48	0.99	0.73
	(0.08)	(0.05)	(0.13)	(0.05)
a_s	7.61	13.29		3.39
	(8.50)	(1.93)		(14.86)
a_e	6.62	8.68	9.92	5.35
	(0.76)	(0.90)	(0.24)	(0.68)
η_s	3.74	3.87		2.34
	(2.27)	(0.41)		(4.07)
η_e	3.57	2.85	5.81	2.28
	(0.42)	(0.41)	(0.33)	(0.42)
f_s	0.04	0.07	0.24	0.17
	(0.02)	(0.01)	(0.03)	(0.02)
f_e	0.32	1.18	-0.06	0.13
	(0.03)	(0.13)	(0.05)	(0.03)
TJ_T	13.57	13.85	13.45	13.95
p-value	0.649	0.678	0.815	0.671

Table 1.7 : Means, Standard Deviation, and Autocorrelations of Investment/Capital Ratios, Investment Returns and Stock Returns: US Corp. (Compare to Cochrane (1991), Table 1)

This table reports time series means and standard deviations and autocorrelations for investment-capital ratios, investment returns and stock returns for the US corporate nonfinancial sector from 1953Q1–2005Q2. Investment returns are those generated by the model without investment-specific technological change in Table 1.2. All returns are gross returns. The stock returns are the CRSP value weighted market index deflated with the CPI.

		Investment/Capital Ratios			Investment Returns			Stock
		Structures	Equipment	Total	Structures	Equipment	Levered	Return
Mean		1.32	3.94	2.12	102.78	102.02	102.11	102.04
St Dev		0.18	0.75	0.38	5.02	5.72	6.13	6.41
Autocorr	1	0.97	0.98	0.99	1.00	0.33	0.55	0.33
(by lag)	2	0.93	0.96	0.96	1.00	0.22	0.46	0.01
	3	0.87	0.92	0.93	1.00	0.16	0.33	-0.02
	4	0.81	0.87	0.89	1.00	0.17	0.28	0.00
	5	0.73	0.82	0.84	1.00	0.03	0.19	-0.09
	6	0.66	0.77	0.79	0.99	-0.08	0.11	-0.05
	8	0.55	0.68	0.70	0.99	-0.22	0.04	0.03
	12	0.41	0.59	0.60	0.99	-0.03	0.15	0.06

Table 1.8 : Means, Standard Deviation, and Autocorrelations of Investment/Capital Ratios, Investment Returns and Stock Returns: NASDAQ (Compare to Cochrane (1991), Table 1)

This table reports time series means and standard deviations and autocorrelations for investment-capital ratios, investment returns and stock returns for the NASDAQ sector for the period 1983Q4–2005Q3. Investment returns are those generated by the model with investment-specific technological change in Table 1.2. All returns are gross returns. The stock returns are the NASDAQ value weighted index from CRSP deflated with the CPI.

		Investment/Capital Ratios			Investment Returns			Stock
		Structures	Equipment	Total	Structures	Equipment	Levered	Return
Mean		3.67	4.91	4.57	104.61	103.09	102.46	102.47
St Dev		1.31	1.65	1.05	25.59	11.78	12.63	10.36
Autocorr	1	0.97	0.92	0.89	0.31	-0.12	-0.03	0.22
(by lag)	2	0.96	0.84	0.80	0.41	0.18	0.19	0.02
	3	0.94	0.73	0.67	0.34	0.07	0.02	0.08
	4	0.92	0.64	0.55	0.31	-0.12	-0.11	0.01
	5	0.88	0.56	0.45	0.17	-0.08	-0.07	-0.18
	6	0.86	0.50	0.37	0.20	0.05	0.04	0.02
	8	0.79	0.37	0.21	0.00	-0.23	-0.23	0.03
	12	0.65	0.28	0.04	-0.11	-0.01	-0.05	-0.03

Table 1.9 : Model Generated Stock Return Standard Deviations

This table reports time series standard deviations for stock returns for the US corporate nonfinancial and NASDAQ sectors for the periods 1953Q1–2005Q2, and 1983Q4–2005Q3, respectively. Actual return standard deviations are compared to those predicted by various model specifications to examine the effect of each assumption. Unless otherwise noted, investment specific technological change is used for the NASDAQ but not for the US corporate nonfinancial sector. The specifications are: with homogeneous capital, with investment-specific technological change, without investment-specific technological change, with all equity financing, and with quadratic adjustment costs. The stock returns for the US corporate nonfinancial sector are the CRSP value weighted market index deflated with the CPI. The stock returns are for the NASDAQ come are the NASDAQ value weighted index from CRSP deflated with the CPI.

	US Corporate Nonfinancial	NASDAQ
Actual	6.41%	10.36%
Homogeneous Capital	2.48%	16.59%
Inv. Spec. Tech. Change	6.32%	12.63%
No Inv. Spec. Tech. Change	6.13%	18.70%
All Equity	2.57%	11.53%
Quadratic Adj. Costs	4.32%	10.80%

Table 1.10 : Regression of Real Stock Returns on Investment Returns, Investment Growth, and Growth in Output (Compare to Cochrane (1991), Table 2)

This table reports correlations, t-statistics and p-values for regressions of stock returns on investment returns (r^I_{st}, r^I_{et} and $\widehat{r^S_t}$) , investment growth, and growth in output for the US corporate nonfinancial sector (1953Q1–2005Q2) and the NASDAQ sector (1983Q4–2005Q3). Investment returns for the US corporate nonfinancial sector are those generated by the model without investment-specific technological change in Table 1.2. Investment returns for the NASDAQ are generated using the model with investment-specific technological change in Table 1.2. All returns are gross returns. The stock returns are the CRSP value weighted market index, and the NASDAQ value weighted index deflated with the CPI. Growth in Output is the log-change in value added for the US Corporate sector and log-change in revenues for the NASDAQ.

$$r^S_t = \alpha + \beta \times (\text{Right Hand Variable})_t + \varepsilon_t$$

	Panel A: US Corp. Nonfin.			Panel B: NASDAQ		
RHV	t-stat	%p-value	Corr w/RHS	t-stat	%p-value	Corr w/RHS
r^I_{st}	-0.64	52.2	-0.04	2.84	0.6	0.29
r^I_{et}	3.64	0.0	0.24	2.97	0.4	0.30
$\widehat{r^S_t}$	-0.10	91.8	-0.01	3.67	0.0	0.37
i^s_t-growth	2.73	0.7	0.19	1.36	17.9	0.15
i^e_t-growth	3.60	0.0	0.24	3.01	0.3	0.31
$(i^s_t + i^e_t)$-growth	3.29	0.1	0.22	2.52	1.3	0.26
π_t-growth	6.30	0.0	0.40	1.55	12.6	0.17

Table 1.11 : Productivity and Adjustment Costs

This table reports summary statistics and regression coefficients for the regression $log(A_t/A_{t-1}) = \alpha + \beta_s log(i_t^s/i_{t-1}^s) + \beta_e log(i_t^e/i_{t-1}^e) + e_t$ where A_t is net multifactor productivity in the private non-farm business sector (BLS, Table XG 4c) and i_t^s and i_t^e are real investment in structures and equipment, respectively, by the private non-farm business sector (BEA, Fixed Assets Table 4). Data are annual and cover the period from 1949 through 2007. Panel A presents means, standard deviations, minima and maxima for the growth rates. Panel B presents regression coefficient results, standard errors, t statistics and the R square for the OLS regression.

Panel A: Summary Statistics				
Variable	Mean	St. Dev.	Min	Max
$log(A_t/A_{t-1})$	1.23%	1.82%	-3.60%	6.30%
$log(i_t^s/i_{t-1}^s)$	-0.06%	6.98%	-18.55%	12.20%
$log(i_t^e/i_{t-1}^e)$	1.22%	7.93%	-25.17%	13.27%
Panel B: Regression				
Variable	Coefficient	St. Err.	t Stat.	
Intercept	1.35%	0.21%	6.43	
$log(i_t^s/i_{t-1}^s)$	-2.93%	3.47%	-0.85	
$log(i_t^e/i_{t-1}^e)$	-10.16%	3.06%	-3.32	
R square	25.96%			
Observations	59			
Dep. Var.	$log(A_t/A_{t-1})$			

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CHAPTER II

Can Analyst Coverage Explain Excess Comovement?

2.1 Introduction

Return comovement is a fundamental part of modern asset pricing theory. Without exposure to systematic risk, all assets should earn the risk free rate of return. However, many recent studies have documented the existence of "excess comovement" — or comovement above and beyond that which is predicted by standard models. These papers typically fall into one of two categories: (a) those which identify groups of assets whose returns are correlated after controlling for risk (e.g., Karolyi and Stulz, 1996, and Pasquariello and Kallberg, 2008) and (b) those which find increases in comovement after an event takes place which is not necessarily associated with a change in fundamentals, such as the addition of a stock to an index (e.g., Barberis, et al., 2005, and Boyer, 2007). In this paper, I use both approaches to show that correlated information is another important source of comovement and can be used as a baseline in defining "excessive".

If news about the fundamentals of two stocks is both informative and correlated, the returns of the two stocks will tend to be correlated. Because there is scant data on individual investors' information sets, information-driven comovement has received relatively less attention than alternate sources of comovement. Instead of directly focusing on those consuming information (the investors), I focus my attention on those producing information (the analysts). Analyst forecast data are readily available for a wide range of stocks. Based on a model which ties earnings and earnings forecasts to stock return correlations, I develop an easy-to-calculate, intuitive measure of correlated analyst coverage,

$$N_{ij}/\sqrt{N_i N_j}, \tag{2.1}$$

where N_i and N_j, are the number of analysts covering stocks i, and j, respectively, and N_{ij} is the number of common analysts between the two stocks. I show this measure to be a theoretical proxy for earnings forecast error correlations, and to have practical power in explaining excess comovement. In particular, as correlated analyst coverage increases, comovement increases — both in theory and in practice.

Using method (a) — controlling for risk based on standard asset pricing models — I show that increases in correlated analyst coverage are associated with increases in excess comovement. A 1 percent increase in the correlated information measure is associated with an increase in excess comovement of about 0.3 percent. Analysts tend to cover stocks within the same industry. To the extent that industry is a proxy for risk exposure, the correlated analyst coverage variable could be proxying for risk. However, the positive relation is robust even when controlling for industry. The variable also does not seem to be proxying for correlations in unexpected earnings — which have been shown to be related to abnormal returns.

In a second test of the model, using method (b), I choose an event — the addition of a stock to the S&P500 index — that has been shown to be associated with increased comovement, but that is not necessarily associated with a change in the firm's fundamentals. I show that there is a fundamental change in the information structure associated with the newly added firms after the event. In particular, the number of analysts covering the firms increase on average, and, in particular, these new analysts tend to be those covering other S&P500 stocks. With respect to the stocks in the index, the average correlated analyst coverage measure increases significantly for firms that are added to the index — about 17% within the first quarter after the event. Furthermore, I find a positive cross-sectional relationship between the change in correlated analyst coverage and the change in excess comovement. Pairs of stocks whose sets of analysts become more similar tend to see increases in excess comovement. While the magnitude of the effect is not large enough to explain all of the change in comovement around these events, the effect itself is consistent with the hypothesis that correlations in information are responsible for some level of excess comovement.

In both the standard neoclassical investment model and standard consumption based asset pricing models, when there is perfect information about the current states of the economy, the correlation between any two firms' stocks is based solely on the fundamental risk characteristics of the firm, and expectations about risk factors. However, when noisy signals about future states of the world are introduced, expected returns, covariances, and correlations may be affected. In particular, when the errors in signals about future earnings are positively correlated, the expected conditional correlation of stock returns increase. Expected variances and covariances are functions of the prior beliefs about the states and the noisy signals. Rational Bayesian updating leads to an increase in comovement with increases in error correlations. Even though the errors are known to be correlated, the effects of this correlation cannot be fully erased when forming beliefs.

I focus on the covariance structure of forecast error. However, the forecast itself is an estimate of the sum of idiosyncratic and systematic components. An unexpectedly high forecast could mean that either the systematic state is higher than was expected, the idiosyncratic state is higher, or both. So the signals reveal relevant information about systematic factors. Because this information will affect all stocks, this channel can also drive comovement. Veldkamp (2005) develops a model of excess comovement in a rational expectation equilibrium framework which has a similar aggregated information component. In her model, investors have information about a subset of assets. This generates comovement much the same way that the release of GDP or unemployment forecasts affects the prices of a wide range of assets. The covariance channel used in this paper provides a much stronger, direct effect than the aggregated information nature of earnings forecasts.

The paper proceeds as follows. In section 2, I introduce the model and solve for return correlations with and without earnings forecast signals. In section 3, based on the model, I develop the correlated analyst forecast measure which is a proxy for information correlation. I calibrate the model and generate the testable implications of increasing the correlated analyst coverage. Then, I test the hypothesis that high correlated information is associated with excess comovement using two approaches. In section 4, I conclude.

2.2 Model

I use a neoclassical investment model. Because these models link prices and returns to earnings, they provide a natural framework in which to incorporate earnings forecasts. First, I derive stock return correlations in the model with no signals about earnings, and then I incorporate earnings forecasts and examine the effect of these signals on the correlations.

Firms maximize the present value of future cash flows given the pricing kernel as in the standard neoclassical investment model. at time 0, given the current capital, k_0, the firm chooses the amount of investment i_0 and capital k_1 which will produce output, π_1 at time 1. After the output is produced, it is consumed along with the capital after depreciation, $(1-\delta)k_1$. Capital at time 1 is equal to capital stock at time 0 plus investment minus depreciation:

$$k_1 = k_0(1-\delta) + i_0. \tag{2.2}$$

For simplicity, there are no adjustment costs. Firms maximize the market value of equity with respect to the exogenous pricing kernel, $m_{0,1}$:

$$\max_{\{i_0\}} \{\pi(k_0, x_0, y_{i0}) - i_0 + E_0 [m_{0,1} [\pi(k_1, x_1, y_{i1}) + (1-\delta)k_1]]\} \tag{2.3}$$

The first order condition is:

$$1 = E_0 [m_{0,1} [\pi_1(k_1, x_1, y_{i1}) + (1-\delta)]] . \tag{2.4}$$

As in the standard case, the following relations hold:

$$E_t[m_{0,1} r^I_{0,1}] = 1 \tag{2.5}$$

where $r^I_{0,1}$ is the investment return between periods 0 and 1 and is equal to

$$r^I_{0,1} \equiv \frac{\pi_1(k_1, x_1, y_{i1}) + (1-\delta)}{1}. \tag{2.6}$$

Furthermore,

$$P_0 = E_0 [m_{0,1} [\pi(k_1, x_1, y_{i1}) + (1-\delta)k_1]] , \tag{2.7}$$

where P_0 is the ex-dividend value of equity at period 0. When π_t is linearly homogeneous, we can use the first order condition, (2.4) to get: $P_0 = k_1$. The stock return over this period is:

$$r_{0,1}^S \equiv \frac{\pi(k_1, x_1, y_{i1}) + (1-\delta)k_1}{E_t\left[m_{0,1}\left[\pi(k_1, x_1, y_{i1}) + (1-\delta)k_1\right]\right]} \tag{2.8}$$

Substituting the first order condition, we get the standard results equating stock returns and investment returns over the period 0 to 1. Let's impose some structural form on the functions. Let the production function for the *ith* be as follows:

$$\pi_{it} = \pi(k_{it}, x_t, y_{it}) = (x_t + y_{it})k_{it}, \tag{2.9}$$

where the systematic productivity, x_t, evolves according to:

$$x_{t+1} = \overline{x}(1-\rho_x) + \rho_x x_t + \sigma_x \varepsilon_{t+1}^x, \tag{2.10}$$

where ε_{t+1}^x is an i.i.d. standard normal variable, and the idiosyncratic productivity for firm i, y_{it}, evolves according to:

$$y_{it+1} = \overline{y}_i(1-\rho_{y_i}) + \rho_{y_i} y_{it} + \sigma_{y_i} \varepsilon_{t+1}^{y_i}. \tag{2.11}$$

The implicit assumption behind the structure of this production function is that all firms have the same exposure to the systematic productivity variable. Generalizing this function to allow the risk exposures to vary across stocks or including multiple sources of systematic risk is straightforward. However, for the sake of simplicity, and because I am focusing on "excess" comovement, and will be holding fundamentals constant, I use this simple form. The variable x_t has the following conditional moments:

$$\mu_{x_1|x_0} \equiv E[x_1 \mid x_0] = \overline{x}(1-\rho_x) + \rho_x x_0 \tag{2.12}$$

$$\sigma^2_{x_1|x_0} \equiv Var\left(x_1 \mid x_0\right) = \sigma^2_x \tag{2.13}$$

$$\tag{2.14}$$

and similar for y_{jt}. The pricing kernel is assumed to be of the following form:

$$\log m_{t,t+\tau} = \log \eta^\tau + \gamma(x_t - x_{t+\tau}) \tag{2.15}$$

Correlations without Signals

The variance of the stock return of any firm i from time 0 to time 1 is equal to

$$Var_0(r^i_{0,1}) = Var_0\left(\frac{P_{i1}}{P_{i0}}\right) \tag{2.16}$$

$$= \frac{1}{k^2_{i1}} Var_0(P_{i1}) \tag{2.17}$$

$$= Var_0(x_1 + y_{i1}) \tag{2.18}$$

The covariance of the stock returns of firm i and firm j can be written:

$$Cov_0(r^i_{0,1}, r^j_{0,1}) = \frac{1}{k_{i1}k_{j1}} Cov_0(P_{i1}, P_{j1}) \tag{2.19}$$

$$= Cov_0(x_1 + y_{i1}, x_1 + y_{j1}) \tag{2.20}$$

Thus, the correlation between the two stock returns is

$$\rho_{ij} \equiv Corr_0(r^i_{0,1}, r^j_{0,1}) = \frac{Cov_0(r^i_{0,1}, r^j_{0,1})}{\sqrt{Var_0(r^i_{0,1})Var_0(r^j_{0,1})}} \tag{2.21}$$

$$= \frac{Cov_0(x_1 + y_{i1}, x_1 + y_{j1})}{\sqrt{Var_0(x_1 + y_{i1})Var_0(x_1 + y_{j1})}} \tag{2.22}$$

$$= \frac{\sigma^2_x}{\sqrt{\{\sigma^2_x + \sigma^2_{y_i}\}\{\sigma^2_x + \sigma^2_{y_j}\}}}. \tag{2.23}$$

When the conditional volatility of the systematic productivity variable is large relative to the idiosyncratic volatilities, this correlation will be close to one. When there is a large amount of firm specific productivity uncertainty, this value will be relatively small. If the state variables, x_1, y_{i1} and y_{j1} are partially inferred from some sort of a signal, the correlations may not be the same as in the above case, as is described in the next subsection.

2.2.1 Information

To examine the effects of correlated information on comovement, I introduce correlated signals into the model. At time 0^+, immediately after the firms make their investment decisions, earnings forecasts are released. No investment or production takes place at time 0^+. The only other difference between times 0 and 0^+ is the information set. None of the state variables differ (e.g., $x_0 = x_{0^+}$). The state x_0, y_{i0}, y_{j0} and y_{l0} are known with certainty At times 0 and 0^+. Also, assume that at time 1, the states x_1, y_{i1}, y_{j1} and y_{l1} will be also known with certainty. The earnings forecasts, $\tilde{e}_i$, are of the form $\tilde{e}_i = \pi_{i1} + e_i k_{i1} = (x_1 + y_{i1} + e_i)k_{i1}$, where the forecast error, e_i, is a normal random variable which has a variance σ^2_{ei} and a covariance σ_{eij}. Because the levels of capital are known at time 0^+ – one period in advance – an equivalent forecast is $z_i = x_1 + y_{i1} + e_i$. Using these earnings forecasts at time 0^+, the representative agent prices all stocks based on the known states at time 0^+, and the best estimate of the future states given all of the earnings forecasts.

Correlations with Signals

As already shown, before the earnings forecasts are released (or in the case without earnings forecasts) the market value of equity for firm i, P_{i0} is equal to the optimal capital stock, k_{i1}. At time 1, the value, P_{i1}, is equal to the cash flow plus the non depreciated portion of the capital stock:

$$P_{i1} = (x_1 + y_{i1})k_{i1} + (1 - \delta)k_{i1} \tag{2.24}$$

As soon as the earnings forecasts are released, the price will depend on the signals (earnings forecasts) of all firms:

$$P_{i0^+} = E_{0^+}[m_{0^+,1} P_{i1}]. \tag{2.25}$$

We can solve for this based on the state variables at time 0 and the signals. However, because we are focusing on correlations, we need not do so.

Similar to the case with no earnings forecasts,

$$Var_{0^+}(r^i_{0^+,1}) = \frac{1}{P^2_{i0^+}} Var_{0^+}(P_{i1}) = \frac{k^2_{i1}}{P^2_{i0^+}} Var_{0^+}\left(x_1 + y_{i1}\right) \tag{2.26}$$

$$Cov_{0^+}(r^i_{0^+,1}, r^j_{0^+,1}) = \frac{k_{i1}k_{j1}}{P_{i0^+}P_{j0^+}} Cov_{0^+}\left(x_1 + y_{i1}, x_1 + y_{j1}\right). \tag{2.27}$$

So,

$$\rho^+_{ij} \equiv Corr_{0^+}(r^i_{0^+,1}, r^j_{0^+,1}) = \frac{Cov_{0^+}(x_1 + y_{i1}, x_1 + y_{j1})}{\sqrt{Var_{0^+}(x_1 + y_{i1})Var_{0^+}(x_1 + y_{j1})}}. \tag{2.28}$$

This equation differs from (2.23) only in the information set. If the signals are sufficiently noisy, the two will be close to the same. However, if the signals are informative, the two may differ. The conditional stock return correlation will be a function of the parameters of the state variables and of the signals, and can be determined by solving for the components of (2.28).

2.2.2 Kalman Filter

Due to the linear structure of the model, the Kalman filter algorithm or linear least squares method provides the best estimate of the state variables and their covariances at time 1, given the signals at time 0^+.[1] The Kalman Filter can be applied as follows. the state process, s_t is

$$s_1 = As_0 + B\overline{s} + \varepsilon_t \tag{2.29}$$

with measurements that are

$$z_{0^+} = Cs_1 + e_1. \tag{2.30}$$

In our case, the state variable vector $s_t \in \Re^{n+1}$ is $s_t = (x_t, y_{1t}, y_{2t}, \ldots, y_{nt})'$, where x_t represents the systematic level of productivity and y_{it} is the idiosyncratic component of productivity for firm i and $\overline{s} = (\overline{x}, \overline{y}^1, \overline{y}^2, \ldots, \overline{y}^n)'$. The matrices A, B, and C are as follows:

$$A = \begin{bmatrix} \rho_x & 0 & 0 & \cdots & 0 \\ 0 & \rho_y^1 & 0 & \cdots & 0 \\ 0 & 0 & \rho_y^2 & & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \rho_y^n \end{bmatrix}, \tag{2.31}$$

[1] See Bertsekas (2000) for a detailed discussion of the Kalman filter and its relation to linear regression

$$B = \begin{bmatrix} (1-\rho_x) & 0 & 0 & \cdots & 0 \\ 0 & (1-\rho_y^1) & 0 & \cdots & 0 \\ 0 & 0 & (1-\rho_y^2) & & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & (1-\rho_y^n) \end{bmatrix}, \tag{2.32}$$

$$C = \begin{bmatrix} 1 & 1 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \ddots & \vdots \\ 1 & 0 & 0 & 0 & \cdots & 1 \end{bmatrix}, \tag{2.33}$$

Applying the Kalman filter algorithm to estimate the states, $\hat{s}_1$ and their variance-covariance matrix, Σ:

$$\hat{s}_1 = E[s_1 \mid I_{0+}] = A\hat{s}_0 + B\overline{s} + \Sigma C' N^{-1} \left(z_{t+1} - C\left(A\hat{s}_t + B\overline{s}\right)\right) \tag{2.34}$$

$$\Sigma = E[(s_1 - \hat{s}_1)(s_1 - \hat{s}_1)' \mid I_{0+}] = M - MC'\left(CMC' + N\right)^{-1} CM. \tag{2.35}$$

where M is the $n+1 \times n+1$ diagonal variance-covariance matrix

$$M = \begin{bmatrix} \sigma_x^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{y^1}^2 & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{y^2}^2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{y^n}^2 \end{bmatrix}, \tag{2.36}$$

and N is the $n \times n$ diagonal variance-covariance matrix

$$N = \begin{bmatrix} \sigma^2_{e^1} & \sigma_{e^{1,2}} & \sigma_{e^{1,3}} & \cdots & \sigma_{e^{1,n}} \\ \sigma_{e^{1,2}} & \sigma^2_{e^2} & \sigma_{e^{2,3}} & \cdots & \sigma_{e^{2,n}} \\ \sigma_{e^{1,3}} & \sigma_{e^{2,3}} & \sigma^2_{e^3} & \cdots & \sigma_{e^{3,n}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{e^{1,n}} & \sigma_{e^{2,n}} & \sigma_{e^{3,n}} & \cdots & \sigma^2_{e^n} \end{bmatrix}. \tag{2.37}$$

Given the Σ matrix, we can solve for the predicted conditional stock return correlation at time 0^+: Given the signals at time 0^+, The variances, covariances, and correlations of the stock returns are

$$\rho^+_{12} \equiv Corr^+_0(r^{s1}_{0^+,1}, r^{s2}_{0^+,1}) = \frac{Cov_{0^+}(x_1 + y_{11}, x_1 + y_{21})}{\sqrt{Var_{0^+}(x_1 + y_{11})Var_{0^+}(x_1 + y_{21})}}, \tag{2.38}$$

where

$$Cov_{0^+}(x_1 + y_{i1}, x_1 + y_{j1}) = \Sigma_{1,1} + \Sigma_{1,i+1} + \Sigma_{1,j+1} + \Sigma_{i+1,j+1} \tag{2.39}$$

$$Var_{0^+}(x_1 + y_{i1}) = \Sigma_{1,1} + 2\Sigma_{1,i+1} + \Sigma_{i+1,i+1} \tag{2.40}$$

$$Var_{0^+}(x_1 + y_{j1}) = \Sigma_{1,1} + 2\Sigma_{1,j+1} + \Sigma_{j+1,j+1}, \tag{2.41}$$

and $\Sigma_{k,l}$ denotes the element in the kth row and lth column of Σ. Because Σ is calculated by inverting a matrix, when the number of stocks is large, it becomes difficult to solve symbolically and thus comparative statics are hard to generalize. For this reason, I calibrate the model and show that the stock return correlation between any two stocks increases with the correlation in forecast errors. See the appendix at the end of this chapter for a solution using two firms. After describing the data and introducing a measure of correlated analyst coverage which proxies for correlated forecast errors, I calibrate the model and show numerically that return comovement increases with increases in correlated forecast errors in the next section.

2.3 Data Sources and Variable Construction

I use the unique analyst and broker id numbers from the I/B/E/S (Institutional Brokers' Estimate System) database to determine which analysts are making earnings per share forecasts. I gather stock return and industry SIC code data from the CRSP (Center for Research in Security Prices) database. Data for the 3 Fama French factors and the Carhart momentum factor along with data on additions and subtractions to the S&P500 index are from Wharton Research Data Services.

2.3.1 Correlated Analyst Coverage and Forecast Errors Measure

I am interested in the covariance structure of the earnings forecast errors. It is possible to estimate this matrix directly using realized earnings forecast errors. However, given the staggered nature of both earnings announcement dates and analyst forecast dates, this is a difficult task in practice. Instead of estimating the covariance matrix directly, I take an indirect approach using observable analyst coverage data. Analysts typically use models or standardized methodologies when making projections about earnings. Additionally, many of the inputs used in their models, such as projected GDP- or industry-growth may be used across multiple stocks, and among analysts within the same firm. To the extent that each analyst uses the same methodology, model, and inputs, across stocks we might expect any systematic errors to filter through to the earnings forecasts across stocks for which they make projections.

With this in mind, assume for simplicity that the signal of the ith firm is the simple average of the forecasts of N_i analysts. Also, assume that the forecast error for each analyst is the same regardless of stock and has a variance of σ_a^2 for any stock. Then, the variance of the signal error, e_i, for the ith stock is equal to σ_a^2/N_i. Let $N_{i,j}$ be the number of shared analysts between the ith and jth stocks. Then, the covariance of the forecast errors for stocks i and j is:

$$Cov(e_i, e_j) = \begin{cases} 0 & \text{if } N_{i,j} = 0 \\ \frac{\sigma_a^2}{N_i N_j} & \text{if } N_{i,j} = 1 \\ \frac{2\sigma_a^2}{N_i N_j} & \text{if } N_{i,j} = 2 \\ \vdots & \vdots \\ \frac{min(N_i, N_j)\sigma_a^2}{N_i N_j} & \text{if } N_{i,j} = min(N_i, N_j) \end{cases} \tag{2.42}$$

$$= \frac{N_{i,j}}{N_i N_j}\sigma_a^2 \tag{2.43}$$

and thus the error correlation is:

$$\rho_{ij}^{an} \equiv Corr(e_i, e_j) = \frac{N_{i,j}}{\sqrt{N_i N_j}}. \tag{2.44}$$

This coefficient which ranges between 0 and 1 is similar to measures which have been used to quantify the "similarity" of sets.[2] Thus, this quantity is a practical measure of the similarity of the sets of analysts covering the two stocks and a theoretical measure of the correlation between the forecast errors for the two stocks. Using the I/B/E/S database, this can be easily calculated for any pair of stocks.

Each calendar year, for every pair of stocks listed on the S&P500 index from 1982 through 2007, I calculate the correlated analyst coverage measure, ρ_{ij}^{an}, by counting the number of unique analysts making earnings forecasts in the I/B/E/S database, N_i and N_j, and the number of common analysts within these two groups, $N_{i,j}$. There are about 2.6 million stock pair observations over the 26 year period. The first line of Panel A in Table 2.1 shows the summary statistics for ρ_{ij}^{an}. On average, this variable is about 2.6%. This number is relatively low. However, the standard deviation is

[2]Two popular measures of similarity are Sørensen's (1948) similarity coefficient, $2N_{i,j}/(N_i + N_j)$ and the Jaccard (1901) similarity coefficient, $N_{i,j}/(N_i + N_j - N_{i,j})$. The measure in this paper differs from Sørensen's measure only in the sense that a geometric average is used in lieu of an arithmetic average.

about 7.7%. Analysts tend to specialize in a particular industry. Pairs of firms within the same industry generally have relatively high coefficients. To the extent that analysts working for the same firm use the same methodology, share the same information, they will make similar mistakes in projecting a firm's earnings. With this in mind, I repeat the previous exercise at the brokerage firm level and generate a correlated broker coverage measure, ρ_{ij}^{br}. The second line of Panel A presents the summary statistics for this variable. Not surprisingly, the mean of this coefficient is much larger than the analyst coefficient at about 27%. The standard deviation is about 23%. While individual analysts focus on industries, brokerage firms take a more broad approach. The correlation coefficient between the two measures is 0.34.

2.3.2 Comovement Measures

Excess comovement, ρ_{ij}^{ret}, is defined as the correlation coefficient between two firms' realized alphas using an asset pricing model:

$$\rho_{ij}^{ret} = \sum_{t=1}^{T} e_{it} e_{jt} \tag{2.45}$$

where e_{it} and e_{jt} are the residuals from the asset pricing equation:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1} f_{1t} + \beta_{i1} f_{1t} + \ldots + \beta_{i1} f_{1t} + e_{it}. \tag{2.46}$$

Every calendar year from 1982 through 2007, I find all stocks which are part of the S&P500 index during that entire year and the previous year. The factor loadings, β_{i1}, β_{12}, $\ldots \beta_{Nt}$, are estimated using data from the previous calendar year. Three models are used: the CAPM, the Fama French 3 factor model (FF3 henceforth), which includes the market return, the size factor and the growth factor, and a 4 factor model (FF4 henceforth) which adds the Carhart momentum factor to the Fama French factors. Additionally, ρ_{ij}^{ret} is calculated using raw returns in lieu of residuals.

Panel B of Table 2.1 proved summary statistics for these estimates using daily returns data. There are an average of 474 stocks per year that are part of the index both the current and previous year. That leads to 2,633,944 yearly correlations over the course of the sample, or about 100,000 per year. The average correlation using raw returns is about 0.223. Excess comovement among these S&P500 stocks based on the CAPM is about 0.052 on average, and about 0.103 and 0.116 using the FF3 and FF4 models, respectively. There is some negative excess comovement in some cases, and the maximum for each variable exceeds 94%.

Because daily returns may be subject to microstructure issues like nonsynchronous trading, I also estimate comovement using weekly returns according to the same procedure as with the daily returns. Panel C of Table 2.1 presents the summary statistics. In each case, the average correlations are higher than those calculated using daily returns. The standard deviations are also larger.

2.4 Results

2.4.1 Calibration

In principal the predicted stock return correlation for any two stocks from the model, $Corr_{0^+}(r^i_{0^+,1}, r^j_{0^+,1})$, can be solved symbolically as a function of the underlying parameters. However, when the number of signals is large, this becomes intractable as it involves inverting a matrix which increases with the number of stocks. So solving for partial derivatives when there are 500 stocks becomes infeasible. Therefore, I calibrate the relevant model parameters, σ^2_x, $\sigma^2_{y_i}$, $\sigma^2_{e^i}$ and $\sigma_{e^{ij}}$, and show numerically that the stock return correlation between any two stocks increases with the covariance of the stocks' earning forecast errors.

Because the earnings cycle is typically quarterly, I focus on that frequency. I set the conditional volatility, σ_x, of the systematic productivity process to 0.007, and the conditional volatility, σ_{y^i}, of the firm-specific productivities to 0.3. These quarterly parameters are consistent with Cooley and Cooley and Prescott (1995) and Zhang (2005). I estimate the standard deviation, σ_{e^i} of the forecast error using the realized errors from the quarterly consensus earnings-per-share forecasts for the sample period from 1982 through 2007 for all S&P500 stocks in the I/B/E/S database. The standard deviation of the quarterly earnings per share forecast error during this period is 0.423. Because of the assumption that earnings are a linear function of the capital stock, K, this error needs to be scaled by capital-per-share. Once this adjustment is made, the realized standard deviation is 0.373, which I use as an estimate of σ_{e^i}. Because firms report earnings at different moments in time, the earnings forecast error covariance parameter, $\sigma_{e^{ij}}$, is difficult to estimate directly. However because I am interested in the theoretical effect of changes in this parameter on stock return correlations, I vary this parameter for stocks i and j and fix it for all other pairs of stocks and examine the changes in ρ^{ij} using equation (2.28). I set the error covariances for all other pairs of the 500 stocks used in the procedure such that the error correlations are 0.026 — the sample average value of ρ_{ij}^{an}.

Figure 2.1 shows the results of varying the forecast error correlation on the stock return comovement for two stocks using these assumptions. Panel A shows that comovement increases from close to zero all the way towards one as the error correlation increases. Panel B plots the slope of the curve in Panel A. This is the marginal effect of increasing the error correlation on comovement. This marginal effect is between 0.4 and 0.5 until ρ_{ij}^{an} is increased to above 0.35. When ρ_{ij}^{an} is equal to 0.026, its sample average, $\partial\rho_{ij}^{ret}/\partial\rho_{ij}^{an}$ equals about 0.40.

These results provide the following testable hypothesis: firms with high correlated analyst coverage, ρ_{ij}^{an}, have high comovement ρ_{ij}^{ret}. Specifically, in a regression of comovement on correlated analyst coverage, the coefficient should be positive. According to the calibration, around our sample mean of 0.028, this coefficient should be around 0.40. This hypothesis is tested in the following subsections.

2.4.2 Analyst Coverage and Excess Comovement

To test the hypothesis that increases in correlated analyst coverage are associated with increases in comovement, I regress excess comovement on the correlated analyst and broker coverage variables. The first columns of Panel A in Tables 2.2 through 2.5 present the results of these regressions using each of the four methods to estimate excess comovement. In all four cases, the coefficients are positive and highly significant, ranging between 0.18 and 0.25. These are smaller than the the theoretical value of 0.41 from the calibration exercise. However, this may not be surprising. The assumption which was used in linking correlated analyst coverage and correlated earnings forecast errors provides an upper bound. If an individual analyst's forecast errors across stocks are not perfectly correlated, this number should be lower. In practice, increasing correlated analyst coverage by one percent leads to an increase in excess comovement of 0.18 to 0.25 percent.

An alternative hypothesis that is consistent with these results is that our models are imperfect and analysts tend to cover firms with the same risk characteristics. If this is the case, analyst coverage provides information about risk above and beyond that provided by our models. Individual analysts tend to focus on firms within the same industry. In order to test whether this is what's being captured by my measure, I use the variables SIC2, SIC3, and SIC4, which are indicator variables set to 1 if the two firms share the same 2-, 3-, or 4- digit Standard Industry Classification codes, and 0 otherwise. The second through fifth columns present the results when controlling for industry affiliation. Again, in each case, the coefficient on the correlated analyst coverage variable is positive and significant, though magnitudes are smaller, ranging between 0.11 and 0.19 once controlling for all three industry-level measures. To the extent that these industries control for risk, correlated analyst coverage increases comovement above and beyond that explained by common industry. Depending on the measure of comovement, stocks within the same 2-digit SIC industry exhibit comovement that is between 6% and 9% higher than those with different SIC codes. Not surprising, once the industry classification is refined, these numbers increase to between 13% and 16% for the stocks within the same 3-digit SIC industry, and to between 13% and 18% for stocks within the same 4-digit SIC industry.

The last five columns of Panel A repeat the results from the regressions in the first five columns with the addition of year fixed effects. The qualitative results are the same as before. However, the coefficients of the analyst variable are larger in magnitude — as high as 29.6% — and the Adjusted R Square statistics are much larger — as high as 0.49.

Individual analysts tend to cover a small percentage of the entire universe of stocks. Any given brokerage firm with, however, may have analysts covering a much larger percentage of the S&P500 firms. To the extent that analysts working for the same firm use similar methodology, information, predictions, or process information in the same manner, we might expect their forecast errors to be correlated. The correlated broker coverage variable, ρ_{ij}^{br}, may provide additional power in explaining excess comovement. To test this hypothesis I repeat the regression in Panels A replacing the analyst level variable with the brokerage level measure. These results are in Panel B of tables 2.2 through 2.5. The coefficients on the brokerage variable are all positive and significant, ranging from about 0.01 to 0.17 with the highest coefficients when comovement is estimated using FF3 and FF4.

In Panel C of the four tables, I test whether both the correlated broker coverage and correlated analyst coverage variables are important. I repeat the same regressions as before but include both variables. The coefficients on ρ_{ij}^{an} are generally greater than those on ρ_{ij}^{br}, except for in a few cases in FF3 and FF4 when ρ_{ij}^{an} actually becomes negative when the industry dummies are included without the year fixed effects. When year fixed effects are included, the magnitude of the broker coefficient is greatly diminished, becoming negative in most cases.

2.4.3 Unexpected Earnings and Excess Comovement

Studies by Chan, Jegadeesh and Lakonishok (1996), and Chordia and Shivakumar (2006) have documented a positive relation between standardized unexpected earnings (SUE, Foster, Olsen, and Shevlin, 1984) and abnormal returns. SUE is calculated as

$$\mathrm{SUE}_{it} = \frac{eps_{iq} - eps_{iq-4}}{\sigma_{it}}, \tag{2.47}$$

where eps_{iq} is the most recent quarterly earnings per share announcement and σ_{it} is the estimated standard deviation of unexpected earnings, $eps_{iq} - eps_{iq-4}$, over the previous 8 quarters. To the extent that similar stocks are followed by similar analysts and experience similar patterns of unexpected earnings, the analyst coverage measure may be simply proxying for the correlation in unexpected earnings. To test this, I estimate the correlation in unexpected earnings, ρ_{ij}^{ue}, for every pair of S&P500 stocks for which sufficient data are available and examine the effect of this variable on the significance of the coefficients of ρ_{ij}^{an} and ρ_{ij}^{br} in explaining excess comovement.

For each calendar year from 1990 to 2007, I estimate ρ_{ij}^{ue} using the previous five years worth of quarterly earnings data. I restrict the sample to those S&P500 stocks that are listed on the index during the entire period and for which there are no missing earnings data. For every pair of stocks that meet these criteria, I estimate correlation coefficients using a 16-quarter time series of unexpected earnings, $eps_{iq} - eps_{iq-4}$. Because I focus on correlations, standardizing the unexpected earnings is less important. During this 18 year period, there are an average of 259 stocks per year that are included in the analysis. That leads to 608,125 estimates of ρ_{ij}^{ue}. Panel D of Table 2.1 shows the summary statistics. This variable has a positive mean of about 6%, a standard deviation of 35% and a very wide range. The variable itself has correlations of 4.9% and 3.8% with ρ_{ij}^{an} and ρ_{ij}^{br}, respectively. While these numbers are not large in magnitude, they are highly statistically significant.

Tables 2.6 through 2.9 present the results of regressing excess comovement on various combinations of the analyst and broker coverage variables and the correlation in unexpected earnings, ρ_{ij}^{an}, along with other control variables. As shown in the first column of Panel A in each of these four tables, the inclusion of ρ_{ij}^{ue} in the regression does decrease the magnitude of the coefficient of ρ_{ij}^{an}, which ranges between 7% and 22%. However, the statistical significance remains. With the introduction of year fixed effects – as seen in the fifth columns – the coefficients of the correlated analyst coverage actually become larger than they were in the longer sample without the inclusion of ρ_{ij}^{ue}, ranging between 27% and 33%. Adjusted R Squares are as high as 0.575.

Panel B of the four tables shows the results from regressing excess comovement on the broker level variable and the unexpected earnings variable. Relative to the previous case, the coefficients on the broker variable are larger across the board. The inclusion of the unexpected earnings correlation seems to strengthen the results. In Panel C, the analyst and broker correlation measures and the unexpected earnings correlation are all included in the regressions. The results are mixed. However, there is little evidence that the correlated analyst and broker coverage variables are proxying for unexpected earnings correlation.

2.4.4 Weekly Returns

Because daily data might be subject to microstructure issues such as nonsynchronous trading, I also use weekly data. Tables 2.10 through 2.13 present the results using weekly data to repeat the regressions from Tables 2.2 through 2.5. The results are very similar to those done at the daily frequency. The average coefficient on ρ_{ij}^{an}

in the simple univariate regression varies from 21% to 26%. As was the case with the daily comovement results, the addition of the industry controls diminishes the magnitude of the coefficients, but the results are qualitatively the same. However, only once does the coefficient of the analyst variable become negative. The addition of year fixed effects increases the magnitudes of the coefficients and the overall fit. The brokerage level variables have a positive, significant effect on comovement until year fixed effects and the analyst level variable are included.

As was the case with the daily data, the inclusion of unexpected earnings correlation in the regressions slightly diminishes the marginal effect of correlated analyst coverage in explaining excess comovement when no year fixed effects are included, and strengthens the effect with the inclusion of year fixed effects. Using weekly data, the results are more consistent and the magnitudes larger. The coefficient on ρ_{ij}^{an} is as large as 38% when year fixed effects are included.

These results suggest that much of the excess comovement we observe is caused by the correlated nature of the information structure. To provide another test of this hypothesis, I examine a case in which the information structure changes for a stock without a change in the stock's underlying fundamental risk structure. Microstructure issues do not seem to be driving the results and may actually be diminishing them.

2.4.5 Additions to the S&P500 Index

Barberis, Shleifer and Wurgler (2005) find that stocks' betas with respect to the S&P500 index tend to increase when they added to that index. They argue that nothing fundamental changes with the stock in the short window over which they estimate these betas and ascribe the increased correlation to the trading behavior of "style investors" – investors who trade stocks based on characteristics or classifications. "Style investors" and institutional investors buying and selling stocks in order to track the S&P500 index are likely to cause an increased in a firm's measured beta. However, there may be another source of comovement. If the if the information structure changes, then we might expect the comovement to change.

Hegde and McDermott (2003) show that additions to the S&P500 index are associated with increases in analyst coverage. If these new analysts are also those covering other S&P500 stocks, the forecast errors may become more correlated. With this in mind, I calculate ρ_{ij}^{an} and ρ_{ij}^{br} each quarter from 12 quarters before to 12 quarters after the event. I use data from the 386 firms from the period 1982 through 2007 which had at least one analyst in the I/B/E/S database before the event. Table 2.18 shows the average values before and after the event, plus the percentage increases, differences, t-statistics and p-values. On average, these measures of correlated information increase when a stock is added to the index. There is a 17% increase in ρ_{ij}^{an} for these new S&P500 stocks from the quarter before to the quarter after the addition. From 12 quarters before to 12 quarters after, there is a 140% increase. The percentage increase in the brokerage variable is similar. Figure 2.2 plots these two variables in event time. There is a distinct break visible at the event date. So on average, the correlated analyst coverage increases with respect to the S&P500 stocks when these stocks are added to the index.

If the increase in correlated information is responsible for some of the increase in return comovement, we would expect this increase to be highest where the increase in correlated analyst coverage is greatest. I regress the changes in excess comovement defined by the four measures on changes in the analyst and brokerage coverage variables from the calendar years before and after the event. Table 2.19 presents the results using 386 firms that are added to the index from 1982 through 2007 for a total of 136291 observations. In the simple regression of $\Delta\rho_{ij}^{ret}$ on $\Delta\rho_{ij}^{an}$, the coefficients using all 4 comovement definitions all between about 5% and 6% and are highly statistically significant. The overall fit of the model, however is fairly low. Most of the total variation in changes in comovement with these firms is not explained by changes in analyst coverage alone. Once year fixed effects are added, however, the total fit does increase, especially in the raw returns case. This is probably capturing some of the changes in market returns during this period. Controlling for the average increase in comovement for each firm, the correlated analyst coverage variable still exhibits a positive relation with comovement. This is shown in the seventh and ninth columns of the table.

Overall, the effects of changes in the correlated analyst coverage on excess comovement are consistently positive and significant around the addition date. Across all specifications which include $\Delta\rho_{ij}^{an}$, its coefficient ranges between 4.3 and 8.7 percent, suggesting that increases in analyst coverage do lead to an increase in comovement that is distinct from changes in fundamental risk characteristics.

2.5 Conclusion

When relevant information is correlated across stocks, the stocks returns will tend to comove more than predicted by standard asset pricing models. This paper develops a new, easy to calculate measure of correlated information based on analyst coverage. A one percent increase in this measure leads to about a 0.4 percent increase in excess comovement. This measure does not seem to be simply a proxy for risk exposure or for correlations in unexpected earnings. The effect is still significant around additions to the S&P500 index where there is a change in the information structure, but not necessarily in the risk exposure does not necessarily. Combined with the standard asset pricing models, this measure provides a benchmark level of comovement against which to define "excess".

2.6 Appendix: Kalman Filter – 2 Stock Example

When the number of stocks is large—as is the case in practice—it is difficult to solve for the variance-covariance matrix of the states symbolically. To give some intuition as to what such a solution might look like, I solve for the two-stock case in this section. In this case, the signals for stocks i and j are $z_i = x_1 + y_{i1} + \sigma_{ei} w_i$ & $z_j = x_1 + y_{j1} + \sigma_{ej} w_j$, which are revealed at time 0^+.

We want to solve for

$$\Sigma = M - MC' \left(CMC' + N\right)^{-1} CM. \tag{2.48}$$

In this case, we have:

$$M = \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_{y^1}^2 & 0 \\ 0 & 0 & \sigma_{y^2}^2 \end{bmatrix} \tag{2.49}$$

$$N = \begin{bmatrix} \sigma_{e^1}^2 & \sigma_{e^{1,2}} \\ \sigma_{e^{1,2}} & \sigma_{e^2}^2 \end{bmatrix} \tag{2.50}$$

$$C = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}. \tag{2.51}$$

Thus,

$$CM = \begin{bmatrix} \sigma_x^2 & \sigma_{y^1}^2 & 0 \\ \sigma_x^2 & 0 & \sigma_{y^2}^2 \end{bmatrix}, \tag{2.52}$$

$$MC' = \begin{bmatrix} \sigma_x^2 & \sigma_x^2 \\ \sigma_{y^1}^2 & 0 \\ 0 & \sigma_{y^2}^2 \end{bmatrix}, \tag{2.53}$$

and

$$(CMC' + N)^{-1} = \frac{1}{D} \begin{bmatrix} \sigma_x^2 + \sigma_{y^2}^2 + \sigma_{e^2}^2 & -(\sigma_x^2 + \sigma_{e^{1,2}}) \\ -(\sigma_x^2 + \sigma_{e^{1,2}}) & \sigma_x^2 + \sigma_{y^1}^2 + \sigma_{e^1}^2 \end{bmatrix}, \tag{2.54}$$

where

$$D = (\sigma_x^2 + \sigma_{y^1}^2 + \sigma_{e^1}^2)(\sigma_x^2 + \sigma_{y^2}^2 + \sigma_{e^2}^2) - (\sigma_x^2 + \sigma_{e^{1,2}})^2. \tag{2.55}$$

Combining these equations, we can solve for Σ:

$$\Sigma_{11} = Var_{0^+}(x_1) = \frac{\sigma_x^2 \left[(\sigma_{y^1}^2 + \sigma_{e^1}^2)(\sigma_{y^2}^2 + \sigma_{e^2}^2) - (\sigma_{e^{1,2}})^2 \right]}{D} \tag{2.56}$$

$$\Sigma_{22} = Var_{0^+}(y_1) = \frac{\sigma_{y^1}^2 \left[(\sigma_x^2 + \sigma_{e^1}^2)(\sigma_{y^2}^2 + \sigma_{e^2}^2) + \sigma_x^2 \sigma_{e^1}^2 - \sigma_{e^{1,2}}(\sigma_{e^{1,2}} + 2\sigma_x^2) \right]}{D} \tag{2.57}$$

$$\Sigma_{33} = Var_{0^+}(y_2) = \frac{\sigma_{y^2}^2 \left[(\sigma_x^2 + \sigma_{e^2}^2)(\sigma_{y^1}^2 + \sigma_{e^1}^2) + \sigma_x^2 \sigma_{e^2}^2 - \sigma_{e^{1,2}}(\sigma_{e^{1,2}} + 2\sigma_x^2) \right]}{D} \tag{2.58}$$

$$\Sigma_{12} = Cov_{0^+}(x_1, y_1) = -\frac{\sigma_x^2 \sigma_{y^1}^2 (\sigma_{y^2}^2 + \sigma_{e^2}^2 - \sigma_{e^{1,2}})}{D} \tag{2.59}$$

$$\Sigma_{13} = Cov_{0^+}(x_1, y_2) = -\frac{\sigma_x^2 \sigma_{y^2}^2 (\sigma_{y^1}^2 + \sigma_{e^1}^2 - \sigma_{e^{1,2}})}{D} \tag{2.60}$$

$$\Sigma_{23} = Cov_{0^+}(y_1, y_2) = \frac{\sigma_{y^1}^2 \sigma_{y^2}^2 (\sigma_x^2 + \sigma_{e^{1,2}})}{D} \tag{2.61}$$

where Σ_{ij} is the element in the ith row and jth column of Σ.

Given the signals at time 0^+, The variances, covariances, and correlations of the stock returns are

$$\rho_{12}^{+} \equiv Corr_0^{+}(r_{0^+,1}^{s1}, r_{0^+,1}^{s2}) = \frac{Cov_{0^+}(x_1 + y_{11}, x_1 + y_{21})}{\sqrt{Var_{0^+}(x_1 + y_{11}) Var_{0^+}(x_1 + y_{21})}}, \tag{2.62}$$

where

$$Cov_{0^+}(x_1 + y_{11}, x_1 + y_{21}) = \Sigma_{11} + \Sigma_{12} + \Sigma_{13} + \Sigma_{23} \tag{2.63}$$

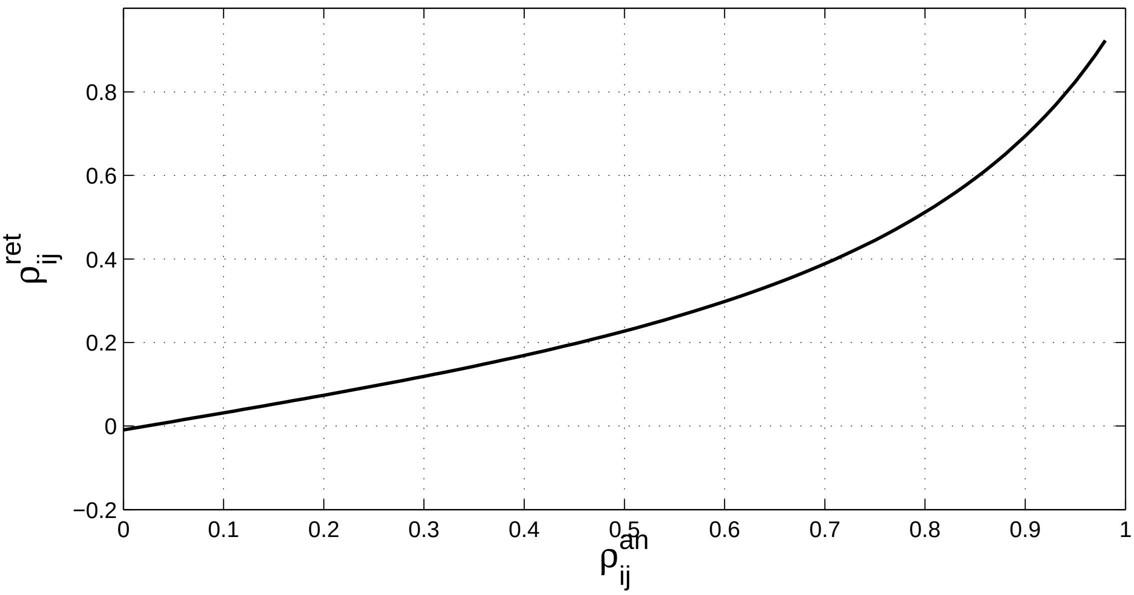
$$Var_{0^+}(x_1 + y_{11}) = \Sigma_{11} + 2\Sigma_{12} + \Sigma_{22} \tag{2.64}$$

$$Var_{0^+}(x_1 + y_{21}) = \Sigma_{11} + 2\Sigma_{13} + \Sigma_{33}. \tag{2.65}$$

Figure 2.1 : Comovement and Correlated Forecast Errors

These panels show the effect of changing the forecast error correlation on return comovement in the model. Panel A plots the error correlation variable, ρ_{ij}^{an} against the return correlation ρ_{ij}^{ret}. Panel B plots the slope of this line, $\partial\rho_{ij}^{ret}/\partial\rho_{ij}^{an}$. In the calibration, σ_x is set to 0.007, σ_y to 0.3, σ_{e^i} to 0.373, and $\sigma_{e^{ij}}$ to 0.028 for all stocks. Then the $\sigma_{e^{ij}}$ is varied between 0 and 0.373^2 for two stocks and ρ_{ij}^{ret} is then calculated for these two stocks.

Panel A: Return Correlations and Correlated Forecast Errors



Panel B: Changes in Return Correlations and Correlated Forecast Errors

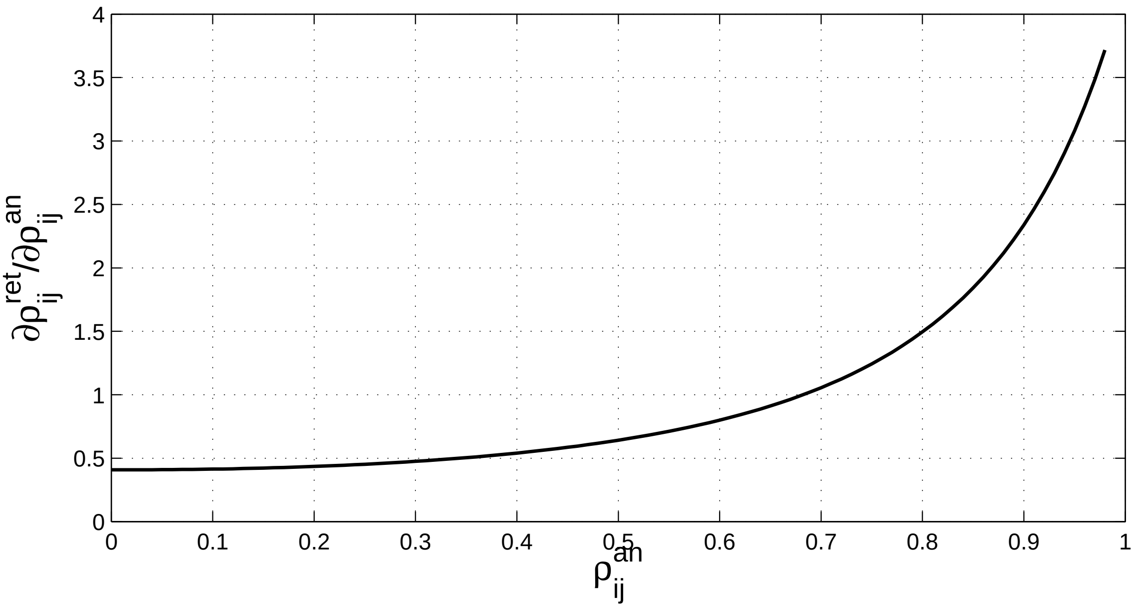
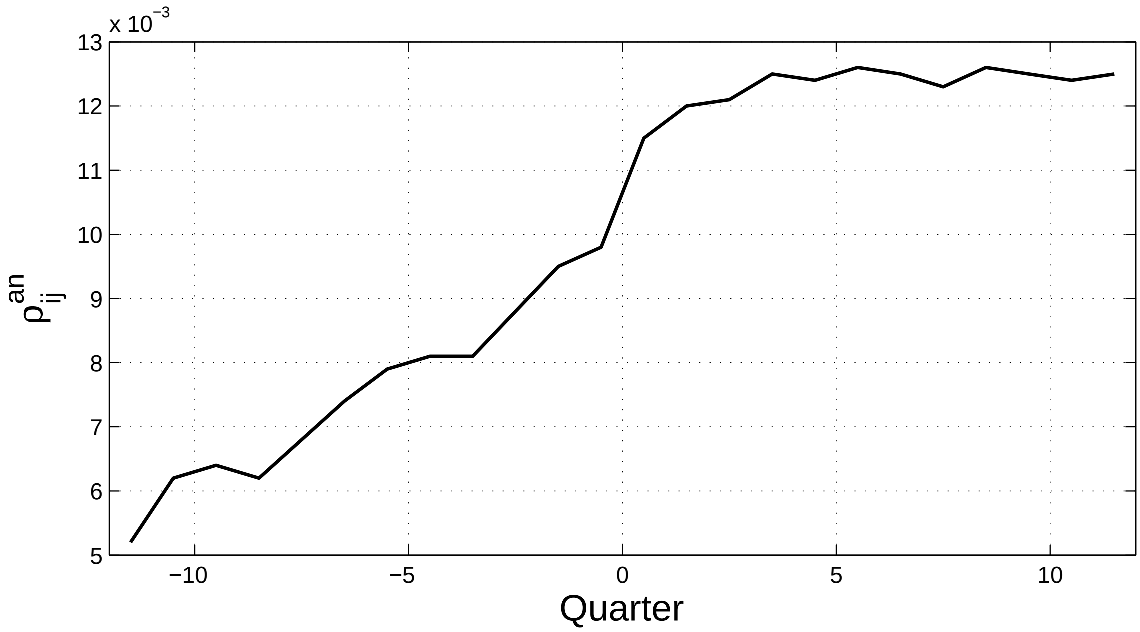


Figure 2.2 : Correlated Analyst and Brokerage Coverage - Additions to S&P500

These panels present average correlated analyst, ρ_{ij}^{an} (Panel A), and broker, ρ_{ij}^{br} (Panel B), coverage between firms added to the S&P500 index from 1982 through 2007 and all other S&P500 firms by quarter from the 12th quarter before the addition date to the 12th quarter after the date. Analyst and broker data are from the I/B/E/S database. S&P500 constituent data are from CRSP. The values plotted in these graphs are found in Table 2.18.

Panel A: Correlated Analyst Coverage



Panel B: Correlated Broker Coverage

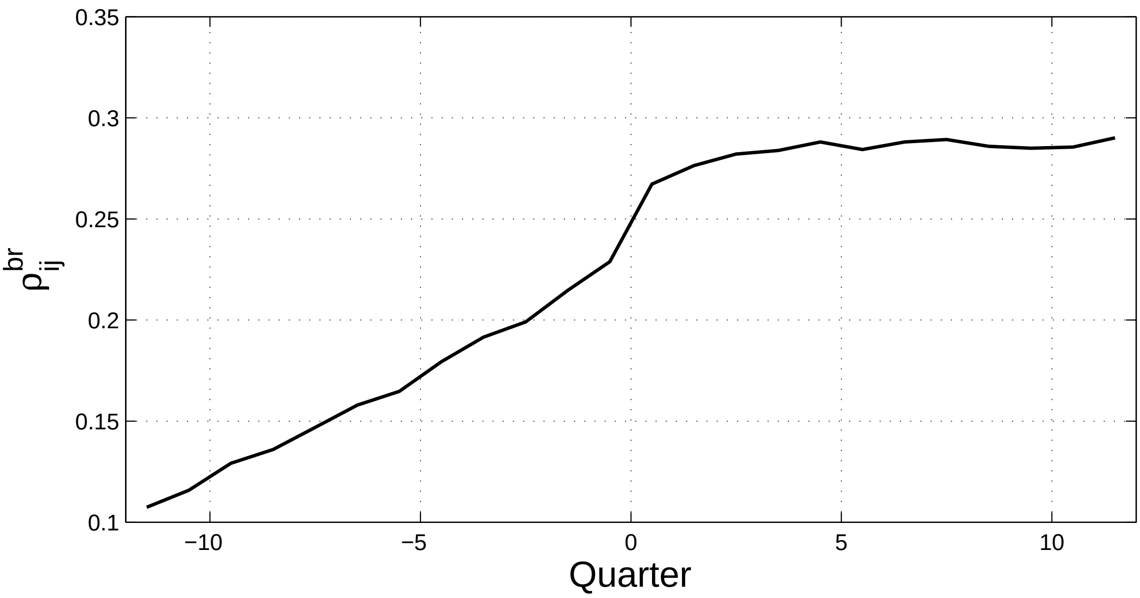


Table 2.1 : Summary Statistics

This table reports summary statistics for the correlated analyst coverage variables and the stock return correlation coefficients for pairs of S&P500 stocks from the period 1982–2007. Panel A presents the correlated analyst coverage measure, ρ_{ij}^{an}, which is defined in equation (2.44), and the correlated brokerage coverage measure, in which brokers are used in lieu of analysts. The correlation coefficients used in Panels B and C are estimated using raw returns, and residuals from the CAPM, the Fama French 3 factor model, and the Fama French 3 factor model plus the Carhart momentum factor. The three models are fit using one year's worth of daily or weekly data and are applied to the following year's data to estimate the correlation coefficients. Analyst data are from the I/B/E/S database, stock returns are from CRSP, and the Fama French and Carhart factor data are from WRDS. Means, standard deviations, minima and maxima are expressed in percentage terms.

Panel A: Analysts and Brokers					
Variable	N	Mean	St. Dev	Min	Max
ρ_{ij}^{an}	2633944	3.8	7.7	0.0	100.0
ρ_{ij}^{br}	2633944	27.4	23.2	0.0	100.0
Panel B: Daily Stock Return Correlations					
Input	N	Mean	St. Dev	Min	Max
raw returns	2633944	22.3	14.0	-34.7	96.2
CAPM alphas	2633944	5.2	12.4	-56.4	94.2
FF alphas	2633944	10.3	16.7	-54.4	94.3
FF+Carhart alphas	2633944	11.6	16.9	-54.3	95.6
Panel C: Weekly Stock Return Correlations					
Input	N	Mean	St. Dev	Min	Max
raw returns	2633944	24.0	18.3	-58.1	98.0
CAPM alphas	2633944	9.5	19.6	-74.2	97.4
FF alphas	2633944	18.0	22.4	-65.7	97.4
FF+Carhart alphas	2633944	22.7	22.3	-65.4	97.5
Panel D: Unexpected Earnings Correlation					
Input	N	Mean	St. Dev	Min	Max
ρ_{ij}^{ue}	608125	5.9	35.0	-99.3	99.5

Table 2.2 : Excess Comovement - Raw Returns (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using daily raw stock returns from CRSP for every pair of S&P 500 stocks that is in the index during the calendar year along with the previous year. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	20.2	15.5	15.0	16.0	13.5	25.0	20.9	20.5	21.2	19.1
	(182)	(134)	(130)	(140)	(116)	(284)	(228)	(223)	(233)	(205)
sic2		6.2			3.6		5.3			3.1
		(134)			(64)		(145)			(70)
sic3			11.5		5.1			9.9		3.9
			(147)		(40)			(161)		(38)
sic4				13.4	5.4				11.9	5.6
				(133)	(36)				(151)	(47)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.012	0.019	0.021	0.019	0.023	0.391	0.396	0.397	0.397	0.399
Panel B: Brokers										
ρ_{ij}^{br}	7.2	6.8	6.8	6.9	6.7	3.8	3.5	3.5	3.5	3.3
	(194)	(185)	(185)	(187)	(183)	(123)	(112)	(112)	(114)	(109)
sic2		7.7			4.3		7.7			4.4
		(172)			(79)		(217)			(101)
sic3			13.8		5.8			13.7		5.3
			(186)		(45)			(233)		(52)
sic4				16.4	6.5				16.6	7.1
				(170)	(43)				(217)	(60)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.014	0.025	0.027	0.025	0.030	0.376	0.387	0.389	0.387	0.392
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	14.6	9.4	8.8	9.9	7.1	24.4	19.9	19.4	20.2	17.9
	(124)	(77)	(72)	(81)	(58)	(256)	(200)	(194)	(204)	(177)
ρ_{ij}^{br}	5.5	5.8	5.8	5.8	5.9	0.6	0.9	1.0	0.9	1.1
	(141)	(148)	(150)	(149)	(152)	(17)	(27)	(30)	(28)	(33)
sic2		6.6			3.8		5.4			3.1
		(141)			(69)		(147)			(71)
sic3			12.1		5.3			10.0		3.9
			(156)		(41)			(163)		(39)
sic4				14.2	5.9				12.0	5.7
				(141)	(39)				(152)	(48)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.020	0.027	0.029	0.027	0.031	0.391	0.396	0.397	0.397	0.399

Table 2.3 : Excess Comovement - CAPM Alphas (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the daily residuals from the CAPM for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Betas for the CAPM are estimated using data from the previous year. Returns data are from CRSP. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	24.2	17.8	17.8	18.9	15.5	27.3	21.2	21.3	22.2	19.0
	(247)	(175)	(175)	(187)	(151)	(300)	(224)	(225)	(236)	(199)
sic2		8.5			5.6		8.0			5.3
		(208)			(114)		(210)			(119)
sic3			14.2		4.7			13.0		3.4
			(208)		(42)			(205)		(33)
sic4				17.0	7.7				16.0	8.2
				(193)	(58)				(197)	(67)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.023	0.039	0.038	0.036	0.044	0.174	0.188	0.187	0.186	0.193
Panel B: Brokers										
ρ_{ij}^{br}	6.9	6.4	6.5	6.6	6.3	2.4	1.8	1.9	2.0	1.7
	(212)	(199)	(199)	(203)	(196)	(73)	(58)	(60)	(62)	(54)
sic2		10.3			6.5		10.4			6.7
		(262)			(135)		(286)			(151)
sic3			17.1		5.6			17.2		4.9
			(262)		(50)			(282)		(47)
sic4				20.7	9.0				21.1	9.8
				(244)	(68)				(267)	(80)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.017	0.042	0.042	0.038	0.050	0.148	0.173	0.173	0.170	0.182
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	19.4	12.4	12.4	13.5	9.8	28.9	22.4	22.5	23.4	20.0
	(187)	(116)	(115)	(127)	(90)	(294)	(219)	(219)	(230)	(192)
ρ_{ij}^{br}	4.7	5.1	5.1	5.1	5.3	-1.5	-1.0	-1.0	-1.1	-0.8
	(137)	(149)	(149)	(148)	(154)	(-44)	(-30)	(-29)	(-31)	(-24)
sic2		8.8			5.8		7.9			5.3
		(216)			(119)		(208)			(118)
sic3			14.8		4.9			12.8		3.4
			(216)		(44)			(203)		(33)
sic4				17.7	8.1				15.8	8.1
				(201)	(62)				(194)	(67)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.030	0.047	0.047	0.044	0.053	0.175	0.188	0.187	0.186	0.193

Table 2.4 : Excess Comovement - FF 3 Factor Alphas (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the daily residuals from the Fama French 3 factor model for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the Fama French model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	18.6	12.1	11.9	13.3	9.7	25.6	19.9	20.0	20.8	17.9
	(140)	(87)	(86)	(96)	(69)	(263)	(196)	(197)	(207)	(174)
sic2		8.8			5.5		7.4			5.0
		(156)			(82)		(183)			(104)
sic3			15.2		6.5			12.1		3.0
			(162)		(43)			(178)		(27)
sic4				17.3	6.3				15.0	7.9
				(143)	(35)				(172)	(60)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.007	0.017	0.017	0.015	0.020	0.482	0.488	0.488	0.487	0.491
Panel B: Brokers										
ρ_{ij}^{br}	16.2	15.8	15.8	15.9	15.6	3.0	2.5	2.5	2.6	2.4
	(373)	(364)	(365)	(367)	(362)	(86)	(73)	(74)	(76)	(69)
sic2		9.2			5.5		9.7			6.2
		(175)			(86)		(249)			(131)
sic3			15.8		6.3			15.9		4.3
			(181)		(42)			(245)		(39)
sic4				18.6	7.0				19.7	9.3
				(164)	(40)				(233)	(72)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.050	0.061	0.062	0.060	0.065	0.469	0.482	0.481	0.480	0.486
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	2.5	-5.2	-5.5	-4.0	-8.1	26.2	20.0	20.1	20.9	17.8
	(18)	(-36)	(-38)	(-28)	(-56)	(249)	(182)	(183)	(192)	(159)
ρ_{ij}^{br}	15.9	16.3	16.3	16.3	16.5	-0.5	-0.1	0.0	-0.1	0.1
	(345)	(355)	(356)	(355)	(360)	(-14)	(-2)	(-1)	(-3)	(3)
sic2		9.7			6.1		7.4			5.0
		(178)			(94)		(182)			(104)
sic3			16.9		6.9			12.1		3.0
			(184)		(46)			(178)		(27)
sic4				19.5	7.7				15.0	7.9
				(165)	(44)				(172)	(61)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.050	0.062	0.062	0.060	0.066	0.482	0.488	0.488	0.487	0.491

Table 2.5 : Excess Comovement - FF 3 Factor + Carhart Alphas (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the daily residuals from an asset pricing model using the 3 Fama French factors and the Carhart momentum factor for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the asset pricing model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	20.5	14.3	14.1	15.4	12.0	25.5	20.0	20.1	20.8	18.0
	(153)	(102)	(100)	(111)	(84)	(260)	(195)	(195)	(204)	(173)
sic2		8.3			5.1		7.2			4.8
		(146)			(76)		(176)			(99)
sic3			14.4		6.2			11.9		3.1
			(152)		(40)			(174)		(27)
sic4				16.5	6.1				14.8	7.8
				(135)	(34)				(168)	(59)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.009	0.017	0.017	0.016	0.020	0.483	0.489	0.489	0.489	0.492
Panel B: Brokers										
ρ_{ij}^{br}	15.0	14.6	14.6	14.7	14.5	3.0	2.5	2.6	2.7	2.4
	(341)	(332)	(332)	(335)	(330)	(87)	(74)	(75)	(77)	(71)
sic2		9.0			5.4		9.5			6.1
		(170)			(83)		(242)			(126)
sic3			15.7		6.3			15.8		4.4
			(176)		(42)			(240)		(39)
sic4				18.5	7.0				19.5	9.3
				(160)	(39)				(228)	(70)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.042	0.053	0.053	0.051	0.056	0.472	0.483	0.483	0.482	0.487
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	5.9	-1.3	-1.6	-0.2	-4.1	26.0	20.0	20.0	20.8	17.8
	(42)	(-9)	(-11)	(-1)	(-27)	(245)	(180)	(180)	(189)	(157)
ρ_{ij}^{br}	14.4	14.7	14.8	14.7	14.9	-0.5	0.0	0.0	0.0	0.2
	(306)	(316)	(317)	(315)	(320)	(-12)	(0)	(1)	(-1)	(5)
sic2		9.2			5.7		7.2			4.8
		(164)			(86)		(176)			(99)
sic3			16.0		6.6			11.9		3.1
			(172)		(43)			(174)		(27)
sic4				18.5	7.3				14.8	7.8
				(154)	(41)				(168)	(59)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.043	0.053	0.053	0.051	0.057	0.483	0.489	0.489	0.489	0.492

Table 2.6 : Excess Comovement and Unexpected Earnings - Raw Returns (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using daily raw stock returns from CRSP for every pair of S&P 500 stocks that is in the index during the calendar year along with the previous year. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	12.9	7.6	7.8	8.3	5.2	27.4	24.7	25.0	24.9	23.4
	(71)	(39)	(40)	(43)	(26)	(189)	(156)	(158)	(160)	(144)
ρ_{ij}^{ue}	3.1	3.1	3.1	3.1	3.1	2.3	2.3	2.3	2.4	2.3
	(63)	(62)	(63)	(63)	(63)	(60)	(60)	(60)	(60)	(60)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.015	0.023	0.023	0.023	0.027	0.399	0.401	0.401	0.401	0.402
Panel B: Brokers										
ρ_{ij}^{br}	13.5	12.3	12.3	12.4	11.8	10.5	9.3	9.3	9.3	8.8
	(112)	(101)	(101)	(102)	(97)	(108)	(95)	(95)	(96)	(90)
ρ_{ij}^{ue}	3.1	3.0	3.0	3.1	3.0	2.6	2.5	2.5	2.6	2.5
	(62)	(61)	(61)	(62)	(61)	(65)	(64)	(64)	(64)	(63)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.027	0.037	0.036	0.036	0.041	0.376	0.386	0.385	0.385	0.390
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	8.1	3.1	3.3	3.9	0.9	24.9	22.2	22.5	22.5	21.0
	(44)	(15)	(17)	(20)	(4)	(165)	(136)	(138)	(139)	(125)
ρ_{ij}^{br}	12.0	11.8	11.8	11.8	11.7	5.7	5.6	5.6	5.6	5.6
	(96)	(95)	(95)	(94)	(94)	(57)	(56)	(56)	(56)	(56)
ρ_{ij}^{ue}	3.0	3.0	3.0	3.0	3.0	2.3	2.3	2.3	2.3	2.3
	(61)	(60)	(61)	(61)	(61)	(59)	(59)	(59)	(59)	(59)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.030	0.038	0.037	0.037	0.041	0.402	0.404	0.404	0.404	0.405

Table 2.7 : Excess Comovement and Unexpected Earnings - CAPM Alphas (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the daily residuals from the CAPM for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Betas for the CAPM are estimated using data from the previous year. Returns data are from CRSP. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	22.0	16.2	17.0	17.6	14.1	32.4	28.2	29.2	29.3	26.9
	(125)	(85)	(89)	(94)	(72)	(201)	(161)	(167)	(170)	(148)
ρ_{ij}^{ue}	1.8	1.7	1.8	1.8	1.7	1.4	1.4	1.4	1.4	1.4
	(36)	(35)	(36)	(36)	(36)	(33)	(33)	(33)	(33)	(33)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.028	0.038	0.035	0.035	0.041	0.239	0.243	0.242	0.242	0.245
Panel B: Brokers										
ρ_{ij}^{br}	12.7	11.0	11.2	11.3	10.5	9.0	7.3	7.4	7.5	6.7
	(106)	(92)	(93)	(94)	(88)	(82)	(67)	(68)	(69)	(62)
ρ_{ij}^{ue}	1.9	1.8	1.8	1.8	1.7	1.8	1.7	1.7	1.7	1.7
	(38)	(36)	(36)	(37)	(36)	(40)	(38)	(39)	(39)	(38)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.021	0.040	0.036	0.035	0.045	0.197	0.217	0.213	0.212	0.222
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	18.3	12.7	13.6	14.2	10.7	31.1	27.0	27.9	28.1	25.6
	(101)	(65)	(69)	(73)	(54)	(185)	(148)	(154)	(157)	(137)
ρ_{ij}^{br}	9.4	9.1	9.2	9.1	9.0	2.9	2.9	2.9	2.8	2.8
	(76)	(74)	(75)	(74)	(73)	(26)	(26)	(26)	(25)	(25)
ρ_{ij}^{ue}	1.7	1.6	1.7	1.7	1.6	1.4	1.4	1.4	1.4	1.4
	(34)	(34)	(34)	(34)	(34)	(32)	(32)	(32)	(33)	(32)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.037	0.047	0.044	0.044	0.049	0.240	0.244	0.242	0.243	0.245

Table 2.8 : Excess Comovement and Unexpected Earnings - FF 3 Factor Alphas (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the daily residuals from the Fama French 3 factor model for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the Fama French model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

					Panel A: Analysts					
ρ_{ij}^{an}	7.6	-0.2	0.5	1.7	-3.2	30.4	26.7	27.8	27.9	25.7
	(29)	(-1)	(2)	(6)	(-11)	(174)	(140)	(146)	(148)	(130)
ρ_{ij}^{ue}	2.8	2.8	2.8	2.8	2.8	1.5	1.5	1.5	1.5	1.5
	(39)	(39)	(39)	(39)	(39)	(32)	(32)	(32)	(32)	(32)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.004	0.013	0.011	0.010	0.015	0.572	0.573	0.572	0.572	0.574
					Panel B: Brokers					
ρ_{ij}^{br}	20.4	19.0	19.1	19.2	18.5	11.3	9.8	10.0	10.1	9.4
	(118)	(109)	(110)	(110)	(106)	(96)	(84)	(85)	(86)	(80)
ρ_{ij}^{ue}	2.6	2.5	2.5	2.5	2.5	1.8	1.7	1.7	1.8	1.7
	(36)	(35)	(35)	(36)	(35)	(38)	(36)	(36)	(37)	(36)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.025	0.032	0.030	0.029	0.033	0.557	0.564	0.563	0.562	0.566
					Panel C: Analysts and Brokers					
ρ_{ij}^{an}	-0.5	-7.9	-7.1	-5.9	-10.6	27.8	24.1	25.2	25.3	23.1
	(-2)	(-28)	(-25)	(-21)	(-36)	(152)	(122)	(127)	(130)	(113)
ρ_{ij}^{br}	20.5	20.2	20.2	20.1	20.0	5.9	5.9	5.9	5.9	5.8
	(114)	(113)	(112)	(112)	(112)	(49)	(49)	(49)	(49)	(49)
ρ_{ij}^{ue}	2.6	2.6	2.6	2.6	2.6	1.5	1.5	1.5	1.5	1.5
	(36)	(36)	(36)	(37)	(36)	(31)	(31)	(31)	(31)	(31)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.025	0.033	0.031	0.030	0.035	0.573	0.575	0.574	0.574	0.575

Table 2.9 : Excess Comovement and Unexpected Earnings - FF 3 Factor + Carhart Alphas (Daily)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the daily residuals from an asset pricing model using the 3 Fama French factors and the Carhart momentum factor for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the asset pricing model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	8.6	1.2	1.8	2.8	-1.7	30.4	26.9	27.8	27.8	25.8
	(33)	(4)	(6)	(10)	(-6)	(174)	(142)	(146)	(148)	(131)
ρ_{ij}^{ue}	3.0	3.0	3.0	3.0	3.0	1.4	1.4	1.4	1.4	1.4
	(42)	(42)	(42)	(42)	(42)	(30)	(30)	(30)	(30)	(30)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.005	0.013	0.011	0.011	0.015	0.573	0.575	0.574	0.574	0.575
Panel B: Brokers										
ρ_{ij}^{br}	18.6	17.2	17.3	17.4	16.8	10.7	9.2	9.3	9.4	8.7
	(107)	(99)	(99)	(100)	(96)	(91)	(78)	(80)	(80)	(74)
ρ_{ij}^{ue}	2.9	2.8	2.8	2.8	2.7	1.7	1.6	1.7	1.7	1.6
	(40)	(39)	(39)	(39)	(39)	(36)	(34)	(35)	(35)	(34)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.022	0.028	0.027	0.026	0.030	0.558	0.565	0.564	0.564	0.567
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	1.4	-5.7	-5.1	-4.0	-8.3	28.1	24.7	25.5	25.6	23.6
	(5)	(-20)	(-18)	(-14)	(-28)	(154)	(125)	(129)	(132)	(116)
ρ_{ij}^{br}	18.4	18.1	18.1	18.1	17.9	5.2	5.2	5.2	5.1	5.1
	(102)	(101)	(101)	(101)	(100)	(43)	(43)	(43)	(43)	(42)
ρ_{ij}^{ue}	2.8	2.8	2.8	2.8	2.8	1.4	1.4	1.4	1.4	1.4
	(40)	(39)	(40)	(40)	(39)	(29)	(29)	(30)	(30)	(29)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.022	0.029	0.028	0.027	0.031	0.575	0.576	0.576	0.576	0.577

Table 2.10 : Excess Comovement - Raw Returns (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using weekly raw stock returns from CRSP for every pair of S&P 500 stocks that is in the index during the calendar year along with the previous year. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	25.8	20.0	20.0	21.1	18.0	29.6	24.2	24.2	25.1	22.3
	(178)	(132)	(132)	(140)	(117)	(220)	(172)	(172)	(180)	(156)
sic2		7.8			5.1		7.1			4.6
		(127)			(70)		(126)			(69)
sic3			12.8		4.5			11.8		3.9
			(126)		(27)			(125)		(26)
sic4				15.1	6.4				14.0	6.3
				(115)	(33)				(116)	(35)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.010	0.021	0.020	0.019	0.024	0.154	0.163	0.161	0.161	0.166
Panel B: Brokers										
ρ_{ij}^{br}	4.9	4.4	4.4	4.5	4.3	4.2	3.7	3.7	3.8	3.6
	(100)	(91)	(91)	(93)	(88)	(88)	(78)	(79)	(81)	(76)
sic2		9.9			6.3		9.8			6.1
		(169)			(87)		(181)			(93)
sic3			16.4		5.6			16.3		5.6
			(168)		(34)			(182)		(36)
sic4				19.6	8.0				19.6	8.1
				(154)	(40)				(168)	(45)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.005	0.021	0.019	0.017	0.025	0.139	0.155	0.153	0.152	0.159
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	23.5	17.3	17.3	18.4	15.1	29.3	23.4	23.3	24.4	21.2
	(153)	(108)	(108)	(115)	(92)	(202)	(154)	(153)	(161)	(137)
ρ_{ij}^{br}	2.2	2.5	2.5	2.5	2.7	0.3	0.7	0.7	0.7	0.9
	(43)	(49)	(49)	(49)	(52)	(5)	(14)	(14)	(13)	(17)
sic2		7.9			5.2		7.1			4.7
		(129)			(72)		(126)			(70)
sic3			13.1		4.5			11.9		4.0
			(128)		(27)			(126)		(26)
sic4				15.5	6.7				14.1	6.4
				(117)	(34)				(117)	(35)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.012	0.023	0.021	0.020	0.026	0.155	0.163	0.162	0.161	0.166

Table 2.11 : Excess Comovement - CAPM Alphas (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the weekly residuals from the CAPM for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Betas for the CAPM are estimated using data from the previous year. Returns data are from CRSP. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	25.9	17.6	18.2	19.4	14.9	32.7	24.9	25.6	26.5	22.5
	(167)	(109)	(112)	(120)	(91)	(224)	(164)	(168)	(176)	(146)
sic2		11.2			7.9		10.1			7.3
		(171)			(102)		(167)			(101)
sic3			17.4		4.2			15.4		2.7
			(159)		(23)			(151)		(16)
sic4				21.2	10.4				19.3	10.5
				(150)	(49)				(148)	(54)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.008	0.013	0.013	0.012	0.015	0.305	0.310	0.309	0.309	0.311
Panel B: Brokers										
ρ_{ij}^{br}	5.7	5.1	5.2	5.3	5.0	2.5	1.8	1.9	2.0	1.7
	(110)	(99)	(100)	(103)	(97)	(48)	(35)	(37)	(39)	(33)
sic2		13.0			8.8		13.0			9.0
		(207)			(115)		(224)			(125)
sic3			20.5		5.0			20.4		4.4
			(196)		(28)			(210)		(26)
sic4				25.2	11.6				25.4	12.4
				(185)	(55)				(201)	(63)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.011	0.019	0.018	0.018	0.021	0.296	0.305	0.304	0.304	0.307
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	22.7	13.7	14.3	15.5	10.8	35.1	26.8	27.5	28.4	24.1
	(137)	(80)	(83)	(91)	(62)	(223)	(163)	(166)	(174)	(144)
ρ_{ij}^{br}	3.2	3.6	3.6	3.6	3.8	-2.2	-1.6	-1.6	-1.7	-1.4
	(57)	(66)	(66)	(66)	(70)	(-40)	(-30)	(-29)	(-31)	(-25)
sic2		11.4			8.1		10.0			7.3
		(174)			(104)		(164)			(101)
sic3			17.8		4.3			15.1		2.6
			(162)		(24)			(149)		(16)
sic4				21.7	10.7				19.0	10.4
				(153)	(51)				(145)	(53)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.014	0.020	0.019	0.019	0.022	0.305	0.310	0.309	0.309	0.311

Table 2.12 : Excess Comovement - FF 3 Factor Alphas (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the weekly residuals from the Fama French 3 factor model for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the Fama French model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	21.8	14.0	14.4	15.6	11.5	30.4	23.6	24.2	24.9	21.4
	(122)	(75)	(77)	(85)	(61)	(203)	(151)	(155)	(160)	(135)
sic2		10.4			7.2		8.9			6.5
		(139)			(81)		(143)			(87)
sic3			16.5		4.6			13.5		1.8
			(131)		(22)			(129)		(11)
sic4				19.9	9.3				17.3	10.1
				(123)	(38)				(129)	(50)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.006	0.013	0.012	0.011	0.015	0.318	0.324	0.323	0.323	0.325
Panel B: Brokers										
ρ_{ij}^{br}	11.8	11.2	11.3	11.4	11.1	3.5	2.9	3.0	3.1	2.8
	(199)	(190)	(191)	(193)	(188)	(66)	(56)	(57)	(59)	(53)
sic2		11.4			7.6		11.6			8.0
		(159)			(86)		(194)			(109)
sic3			18.2		4.9			18.1		3.4
			(152)		(24)			(182)		(20)
sic4				22.3	10.1				22.9	11.9
				(144)	(42)				(177)	(59)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.015	0.024	0.023	0.022	0.027	0.309	0.319	0.317	0.317	0.321
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	11.1	2.4	2.7	4.0	-0.6	31.1	23.7	24.3	25.1	21.3
	(59)	(12)	(14)	(21)	(-3)	(192)	(140)	(143)	(149)	(124)
ρ_{ij}^{br}	10.5	11.0	11.0	11.0	11.2	-0.7	-0.1	-0.1	-0.2	0.1
	(167)	(175)	(175)	(175)	(178)	(-12)	(-2)	(-2)	(-3)	(2)
sic2		11.1			7.6		8.9			6.5
		(148)			(86)		(142)			(87)
sic3			17.7		4.9			13.5		1.8
			(141)		(24)			(129)		(11)
sic4				21.4	10.2				17.3	10.1
				(132)	(42)				(129)	(50)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.016	0.024	0.023	0.023	0.027	0.318	0.324	0.323	0.323	0.325

Table 2.13 : Excess Comovement - FF 3 Factor + Carhart Alphas (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the weekly residuals from an asset pricing model using the 3 Fama French factors and the Carhart momentum factor for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the asset pricing model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 2633944 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	25.8	19.2	19.5	20.4	17.0	29.3	23.1	23.6	24.1	21.0
	(146)	(104)	(106)	(111)	(90)	(196)	(147)	(150)	(155)	(132)
sic2		8.9			6.2		8.2			5.8
		(120)			(70)		(130)			(79)
sic3			14.2		3.5			12.5		1.5
			(114)		(17)			(120)		(9)
sic4				17.4	8.8				16.3	9.9
				(109)	(37)				(121)	(49)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.012	0.018	0.018	0.017	0.020	0.172	0.177	0.177	0.176	0.179
Panel B: Brokers										
ρ_{ij}^{br}	9.9	9.4	9.4	9.5	9.2	3.5	3.0	3.1	3.1	2.9
	(167)	(159)	(160)	(162)	(157)	(67)	(57)	(58)	(59)	(54)
sic2		10.6			7.1		10.8			7.3
		(149)			(81)		(180)			(99)
sic3			17.1		4.3			17.0		3.1
			(144)		(21)			(170)		(18)
sic4				21.2	10.1				21.7	11.6
				(137)	(42)				(167)	(58)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.004	0.014	0.014	0.013	0.018	0.159	0.169	0.169	0.168	0.173
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	17.9	10.5	10.8	11.7	7.9	29.8	23.1	23.5	24.1	20.8
	(95)	(54)	(55)	(60)	(40)	(184)	(136)	(138)	(143)	(120)
ρ_{ij}^{br}	7.8	8.2	8.2	8.2	8.4	-0.5	0.0	0.0	0.0	0.2
	(125)	(132)	(132)	(132)	(135)	(-8)	(0)	(1)	(0)	(4)
sic2		9.4			6.5		8.2			5.9
		(127)			(73)		(130)			(79)
sic3			15.0		3.7			12.5		1.5
			(121)		(18)			(119)		(9)
sic4				18.5	9.5				16.3	9.9
				(116)	(39)				(121)	(49)
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.013	0.019	0.019	0.018	0.021	0.172	0.177	0.177	0.176	0.179

Table 2.14 : Excess Comovement and Unexpected Earnings - Raw Returns (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using weekly raw stock returns from CRSP for every pair of S&P 500 stocks that is in the index during the calendar year along with the previous year. 608125 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	20.1	15.0	15.7	16.1	13.1	30.9	27.5	28.3	28.3	26.4
	(86)	(59)	(62)	(64)	(50)	(138)	(113)	(116)	(118)	(104)
ρ_{ij}^{ue}	3.6	3.5	3.6	3.6	3.5	3.1	3.1	3.1	3.1	3.1
	(55)	(54)	(55)	(55)	(54)	(51)	(51)	(51)	(51)	(51)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.017	0.022	0.021	0.021	0.023	0.158	0.160	0.159	0.159	0.160
Panel B: Brokers										
ρ_{ij}^{br}	10.6	9.1	9.2	9.3	8.6	8.8	7.4	7.5	7.5	6.8
	(66)	(57)	(58)	(58)	(54)	(59)	(49)	(50)	(50)	(45)
ρ_{ij}^{ue}	3.7	3.6	3.6	3.6	3.6	3.5	3.4	3.4	3.4	3.3
	(56)	(55)	(55)	(55)	(55)	(56)	(55)	(55)	(56)	(55)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.013	0.022	0.020	0.019	0.024	0.137	0.146	0.144	0.144	0.148
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	17.1	12.2	12.9	13.4	10.4	-2.0	26.2	26.9	27.0	25.1
	(70)	(47)	(49)	(52)	(39)	(-14)	(103)	(106)	(108)	(96)
ρ_{ij}^{br}	7.5	7.3	7.3	7.3	7.2	-10.4	3.1	3.1	3.0	3.0
	(46)	(44)	(44)	(44)	(44)	(-76)	(20)	(20)	(20)	(19)
ρ_{ij}^{ue}	3.5	3.5	3.5	3.5	3.5	-19.1	3.1	3.1	3.1	3.1
	(54)	(53)	(53)	(54)	(53)	(-142)	(51)	(51)	(51)	(51)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.021	0.025	0.024	0.024	0.026	0.159	0.160	0.160	0.160	0.161

Table 2.15 : Excess Comovement and Unexpected Earnings - CAPM Alphas (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the weekly residuals from the CAPM for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Betas for the CAPM are estimated using data from the previous year. Returns data are from CRSP. 608125 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	24.8	18.2	19.6	20.2	16.2	38.1	33.7	35.2	35.4	32.7
	(94)	(64)	(68)	(72)	(55)	(154)	(125)	(131)	(133)	(117)
ρ_{ij}^{ue}	2.5	2.5	2.5	2.5	2.5	1.8	1.8	1.8	1.8	1.8
	(34)	(34)	(34)	(34)	(34)	(26)	(26)	(26)	(27)	(26)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.017	0.022	0.020	0.020	0.024	0.195	0.198	0.196	0.196	0.198
Panel B: Brokers										
ρ_{ij}^{br}	13.8	12.0	12.2	12.3	11.4	10.4	8.5	8.8	8.9	7.9
	(77)	(66)	(68)	(68)	(63)	(63)	(51)	(53)	(53)	(48)
ρ_{ij}^{ue}	2.6	2.5	2.6	2.6	2.5	2.2	2.1	2.1	2.1	2.0
	(36)	(34)	(35)	(35)	(34)	(32)	(31)	(31)	(31)	(30)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.012	0.023	0.020	0.019	0.025	0.169	0.180	0.178	0.177	0.183
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	20.8	14.4	15.8	16.5	12.6	-1.4	32.3	33.8	34.0	31.3
	(76)	(49)	(54)	(57)	(42)	(-9)	(116)	(121)	(123)	(109)
ρ_{ij}^{br}	10.0	9.8	9.8	9.8	9.7	3.3	3.2	3.2	3.2	3.2
	(54)	(53)	(53)	(53)	(52)	(22)	(19)	(19)	(19)	(19)
ρ_{ij}^{ue}	2.4	2.4	2.4	2.4	2.4	-8.1	1.7	1.7	1.8	1.7
	(33)	(33)	(33)	(33)	(33)	(-54)	(26)	(26)	(26)	(26)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.021	0.027	0.025	0.024	0.028	0.196	0.198	0.197	0.197	0.198

Table 2.16 : Excess Comovement and Unexpected Earnings - FF 3 Factor Alphas (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the weekly residuals from the Fama French 3 factor model for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the Fama French model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 608125 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	17.6	10.5	11.9	12.7	8.3	36.0	32.4	34.0	34.0	31.8
	(56)	(31)	(35)	(38)	(24)	(143)	(118)	(123)	(125)	(111)
ρ_{ij}^{ue}	3.1	3.0	3.0	3.1	3.0	1.7	1.7	1.7	1.7	1.7
	(35)	(35)	(35)	(35)	(35)	(25)	(25)	(25)	(25)	(25)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.007	0.012	0.011	0.010	0.013	0.394	0.395	0.394	0.394	0.395
Panel B: Brokers										
ρ_{ij}^{br}	19.8	18.2	18.4	18.6	17.7	13.6	11.9	12.2	12.3	11.5
	(94)	(86)	(87)	(87)	(83)	(80)	(71)	(72)	(72)	(68)
ρ_{ij}^{ue}	3.0	2.9	2.9	2.9	2.9	2.1	2.0	2.0	2.0	1.9
	(34)	(33)	(34)	(34)	(33)	(30)	(28)	(29)	(29)	(28)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.017	0.022	0.021	0.020	0.024	0.380	0.386	0.384	0.384	0.387
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	10.5	3.8	5.2	6.1	1.9	-11.2	29.2	30.8	30.9	28.7
	(33)	(11)	(15)	(18)	(5)	(-70)	(102)	(108)	(110)	(97)
ρ_{ij}^{br}	17.9	17.6	17.7	17.6	17.5	-22.7	7.1	7.1	7.1	7.1
	(82)	(81)	(81)	(81)	(80)	(-147)	(41)	(41)	(41)	(41)
ρ_{ij}^{ue}	2.9	2.8	2.9	2.9	2.8	-25.6	1.7	1.7	1.7	1.7
	(33)	(33)	(33)	(33)	(33)	(-169)	(24)	(24)	(24)	(24)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.018	0.023	0.021	0.021	0.024	0.395	0.397	0.396	0.396	0.397

Table 2.17 : Excess Comovement and Unexpected Earnings - FF 3 Factor + Carhart Alphas (Weekly)

This table reports OLS regression coefficients and t-statistics from regressing stock return correlations between pairs of stocks on correlated unexpected earnings, ρ_{ij}^{ue}, correlated analyst coverage, ρ_{ij}^{an}, and correlated brokerage coverage, ρ_{ij}^{br}, along with various control variables. SIC2, SIC3, and SIC4 are indicator variables that are equal to 1 if the pair of stocks share the same 2-, 3-, or 4-digit Standard Industry Classification code, respectively, and zero otherwise. Year fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated yearly using the weekly residuals from an asset pricing model using the 3 Fama French factors and the Carhart momentum factor for each pair of S&P 500 stocks that are in the index during the calendar and the previous year. Factor loadings for the asset pricing model are estimated using data from the previous year. Returns data are from CRSP and factor data from WRDS. 608125 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Analysts										
ρ_{ij}^{an}	20.2	14.5	15.5	16.0	12.6	34.3	31.2	32.4	32.3	30.5
	(66)	(44)	(47)	(49)	(37)	(137)	(114)	(119)	(120)	(108)
ρ_{ij}^{ue}	3.3	3.3	3.3	3.3	3.3	1.7	1.7	1.7	1.7	1.7
	(39)	(39)	(39)	(39)	(39)	(26)	(25)	(26)	(26)	(26)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.010	0.013	0.012	0.012	0.014	0.369	0.370	0.369	0.369	0.370
Panel B: Brokers										
ρ_{ij}^{br}	18.1	16.6	16.8	16.9	16.2	12.3	10.8	11.0	11.1	10.4
	(88)	(80)	(81)	(82)	(78)	(74)	(65)	(66)	(66)	(62)
ρ_{ij}^{ue}	3.3	3.2	3.2	3.3	3.2	2.1	2.0	2.0	2.0	2.0
	(39)	(38)	(38)	(39)	(38)	(30)	(29)	(29)	(30)	(29)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.015	0.021	0.019	0.019	0.022	0.355	0.361	0.359	0.359	0.362
Panel C: Analysts and Brokers										
ρ_{ij}^{an}	14.1	8.7	9.7	10.3	7.0	-10.2	28.4	29.7	29.6	27.8
	(45)	(26)	(29)	(31)	(20)	(-64)	(100)	(105)	(106)	(95)
ρ_{ij}^{br}	15.5	15.3	15.3	15.3	15.2	-17.3	6.2	6.2	6.1	6.1
	(73)	(72)	(72)	(72)	(72)	(-112)	(36)	(36)	(36)	(35)
ρ_{ij}^{ue}	3.2	3.1	3.1	3.2	3.1	-8.8	1.7	1.7	1.7	1.7
	(37)	(37)	(37)	(37)	(37)	(-58)	(25)	(25)	(25)	(25)
sic dummy	—	2	3	4	2,3,4	—	2	3	4	2,3,4
Year FE	N	N	N	N	N	Y	Y	Y	Y	Y
Adj. R Sq.	0.019	0.022	0.021	0.021	0.022	0.370	0.371	0.371	0.371	0.371

Table 2.18 : Correlated Analyst Coverage Before and After Additions

This table reports the average correlated analyst coverage measure and correlated broker coverage measure for stocks before and after being added to the S&P500 index, plus the percentage change and difference in these means, and the t-statistic and p-value for these differences. The means are calculated for the 1st quarter before and after the event through the 12th quarter before and after. 386 stocks are used from 1982 through 2007.

Panel A: Using Analysts						
Qtr	Before	After	%Change	Diff	t-stat	p-value
1	0.0098	0.0115	17.3	0.0017	3.39	0.0007
2	0.0095	0.0120	26.3	0.0025	4.64	< 0.0001
3	0.0088	0.0121	37.5	0.0033	6.27	< 0.0001
4	0.0081	0.0125	54.3	0.0044	8.58	< 0.0001
5	0.0081	0.0124	53.1	0.0042	8.25	< 0.0001
6	0.0079	0.0126	59.5	0.0047	8.70	< 0.0001
7	0.0074	0.0125	68.9	0.0052	9.54	< 0.0001
8	0.0068	0.0123	80.9	0.0055	10.82	< 0.0001
9	0.0062	0.0126	103.2	0.0064	12.13	< 0.0001
10	0.0064	0.0125	95.3	0.0061	11.36	< 0.0001
11	0.0062	0.0124	100.0	0.0062	11.30	< 0.0001
12	0.0052	0.0125	140.4	0.0073	13.95	< 0.0001

Panel B: Using Brokers						
Qtr	Before	After	%Change	Diff	t-stat	p-value
1	0.2289	0.2672	16.7	0.0383	5.64	< 0.0001
2	0.2147	0.2764	28.7	0.0617	8.93	< 0.0001
3	0.1991	0.2821	41.7	0.0830	11.93	< 0.0001
4	0.1915	0.2839	48.3	0.0924	13.20	< 0.0001
5	0.1794	0.2881	60.6	0.1087	15.52	< 0.0001
6	0.1647	0.2843	72.6	0.1196	16.66	< 0.0001
7	0.1579	0.2881	82.5	0.1302	18.42	< 0.0001
8	0.1469	0.2893	96.9	0.1424	20.56	< 0.0001
9	0.1360	0.2859	110.2	0.1499	21.55	< 0.0001
10	0.1292	0.2850	120.6	0.1558	22.23	< 0.0001
11	0.1158	0.2855	146.5	0.1697	24.53	< 0.0001
12	0.1074	0.2901	170.1	0.1827	26.81	< 0.0001

Table 2.19 : Excess Comovement: Additions to the SP 500 Index

This table reports OLS regression coefficients and t-statistics from regressing the change in stock return correlations between stocks that are added to the S&P500 index and all other stocks in the index on changes in correlated analyst coverage, $\Delta\rho_{ij}^{an}$, and correlated brokerage coverage, $\Delta\rho_{ij}^{br}$ before and after the addition date. Year and firm fixed effects are included where indicated. The correlated analyst and brokerage coverage variables are calculated using the I/B/E/S database and equation (2.44). The correlation coefficients are estimated using daily raw returns (Panel A), or residuals from the CAPM (Panel B), the Fama French 3 factor model (Panel C) and a model using the Fama French factors plus the Carhart momentum factor (Panel D). Returns data are from CRSP and factor data from WRDS. 136291 observations are used. All coefficients are expressed in percentage terms. t-statistics are in parentheses.

Panel A: Raw Returns									
$\Delta\rho_{ij}^{an}$	5.64		8.61	5.43		7.55	6.02		6.28
	(3.2)		(4.8)	(3.6)		(5.0)	(4.8)		(5.0)
$\Delta\rho_{ij}^{br}$		-4.36	-4.60		-3.06	-3.28		-0.27	-0.47
		(-12.1)	(-12.6)		(-9.7)	(-10.3)		(-0.9)	(-1.6)
Year FE	N	N	N	Y	Y	Y	N	N	N
Firm FE	N	N	N	N	N	N	Y	Y	Y
Adj. R Sq.	0.0001	0.0011	0.0012	0.2817	0.2821	0.2823	0.5095	0.5094	0.5095
Panel B: CAPM Alphas									
$\Delta\rho_{ij}^{an}$	4.92		4.27	4.73		4.34	5.93		4.76
	(3.8)		(3.3)	(3.6)		(3.3)	(3.9)		(3.7)
$\Delta\rho_{ij}^{br}$		1.13	1.01		0.73	0.61		0.47	0.32
		(4.2)	(3.8)		(2.7)	(2.2)		(1.5)	(1.0)
Year FE	N	N	N	Y	Y	Y	N	N	N
Firm FE	N	N	N	N	N	N	Y	Y	Y
Adj. R Sq.	0.0001	0.0001	0.0002	0.0084	0.0083	0.0084	0.0554	0.0553	0.0554
Panel C: Fama French 3-Factor Alphas									
$\Delta\rho_{ij}^{an}$	5.51		5.69	5.38		5.60	5.66		5.70
	(4.6)		(4.7)	(4.5)		(4.6)	(4.7)		(4.7)
$\Delta\rho_{ij}^{br}$		-0.12	-0.27		-0.18	-0.34		0.10	-0.08
		(-0.5)	(-1.1)		(-0.7)	(-1.4)		(0.3)	(-0.3)
Year FE	N	N	N	Y	Y	Y	N	N	N
Firm FE	N	N	N	N	N	N	Y	Y	Y
Adj. R Sq.	0.0002	0.0000	0.0002	0.0018	0.0017	0.0018	0.0162	0.0160	0.0162
Panel D: Fama French 3 Factor + Carhart Alphas									
$\Delta\rho_{ij}^{an}$	5.15		5.33	5.10		5.27	5.30		5.36
	(4.3)		(4.4)	(4.3)		(4.4)	(4.4)		(4.4)
$\Delta\rho_{ij}^{br}$		-0.13	-0.27		-0.11	-0.26		0.06	-0.11
		(-0.5)	(-1.1)		(-0.4)	(-1.0)		(0.2)	(-0.4)
Year FE	N	N	N	Y	Y	Y	N	N	N
Firm FE	N	N	N	N	N	N	Y	Y	Y
Adj. R Sq.	0.0001	0.0000	0.0001	0.0016	0.0014	0.0016	0.0132	0.0130	0.0132

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