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INVESTMENT BEHAVIOR, OBSERVABLE EXPECTATIONS, AND INTERNAL FUNDS

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Abstract

We use earnings forecasts from securities analysts to construct more accurate measures of the fundamentals that affect the expected returns to investment. Using a variety of econometric techniques, including semiparametric estimators, we find that investment responds significantly — in both economic and statistical terms — to our new measures of fundamentals. With our controls for expected future profits, we find that internal funds are uncorrelated with investment spending, even for selected subsamples of firms — those paying no dividends and those without bond ratings — that have been found to be "liquidity constrained" in previous studies.

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1 Introduction

Until recently, the consensus among researchers was that neoclassical fundamentals have little effect on investment (see, e.g., Chirinko 1993). For example, in a well-known study, Summers (1981) finds that a one percent increase in the shadow value of capital increases investment by a paltry 0.02 percent. Furthermore, models derived from neoclassical fundamentals have explained the time-series behavior of investment more poorly than *ad hoc* accelerator or "financial" accelerator models (see, respectively, Bernanke, Bohn, and Reiss 1988; Bernanke, Gertler, and Gilchrist 1996). This result could reflect the consequences of asymmetric information in financial markets: Lenders become more favorably inclined to make loans when a firm's net worth improves, leading to an expansion of business investment. In an important study, Fazzari, Hubbard, and Petersen (1988) use firm-level panel data to try to isolate firms for which investment may be constrained by internal funds. They find that the firms most likely to face liquidity constraints tend to have the highest sensitivity of investment to cash flow. Subsequent empirical research generally confirms this finding (see, e.g., Gertler and Hubbard 1988; Calomiris and Hubbard 1990; Oliner and Rudebusch 1992; Gilchrist and Himmelberg 1995). Indeed, some studies, e.g. Lamont (1997), claim that even the largest companies are liquidity constrained. This literature suggests that neoclassical models of investment perform poorly because many firms are constrained by internal funds. However, we believe that such a conclusion is premature.

A parallel literature, in which studies control more fully for measurement error and allow nonlinearities in marginal adjustment costs, has shown that neoclassical fundamentals are economically and statistically significant determinants of investment. For example, Auerbach and Hassett (1991), Cummins and Hassett (1992), and Cummins, Hassett, and Hubbard (1994) use firm-level panel data to construct tax instruments for changes in tax-adjusted Q and the cost of capital, and find that both variables have sizable effects on investment after major US tax reforms. Cummins, Hassett, and Hubbard (1995) find even larger responses after tax reforms in a sample of firms in 12 industrialized countries. Other studies find that investment responds significantly to average Q at relatively low values of Q but little, if at all, at high values (see, e.g., Abel and Eberly 1996; Barnett and Sakellaris 1995). When this nonlinearity is not incorporated into the econometric estimator, the coefficient estimate on average Q implies incorrectly that fundamentals have a negligible effect in the sample as a whole. Using plant-level data and the user cost series developed by Cummins et al. (1994), Caballero, Engel, and Haltiwanger (1995) also find large effects of neoclassical fundamentals on investment.[1]

The findings of this parallel literature raise questions about the widely accepted view that internal funds are an important determinant of investment. Originally, the motivation for focusing on internal funds came from the empirical failure of neoclassical models. If, however, the refinements suggested in this more recent literature revive the neoclassical view, then those who believe that financial factors drive investment face something of a puzzle. How can the findings that support the neoclassical model be reconciled with the results of many studies that report a strong positive effect of internal funds on investment?

This paper attempts to bridge the gap between these two literatures by building on two observations from the neoclassical strand of this work. First, neoclassical models can be tested properly only if one has good measures for the fundamentals that drive investment. This requirement has not been met by most studies. Indeed, the proxies for fundamentals usually are constructed from a small information set under the restrictive assumption that a single process for forming expectations applies to all firms. However, in the neoclassical model, the effect of recent news on the fundamentals that drive investment will differ importantly across firms (see Cummins et al. 1994). For example, a start-up company that earns profits for the first time might boost investment enormously if the breakthrough signals stronger future fundamentals; in contrast, a mature company in a highly cyclical industry might respond little to a sudden increase in profits, as these have almost no effect on expected future conditions. Valid tests of the relation between investment and liquidity must allow for this heterogeneity in specifying the null neoclassical model. The second observation is that simple linear models may not capture the relationship between investment and its fundamental determinants. Research has shown that fundamentals have very large effects in some

[1]For reviews of this more recent literature, see Caballero (1997) and Hassett and Hubbard (1997).

regions and small effects in others. In linear models, measures of liquidity may simply be proxying for the omitted nonlinearities.

These two considerations motivate our tests of the importance of fundamentals and liquidity. To ensure robustness, we use two variables — net income and cash flow — to measure changes in internal net worth. We then depart from prior work by employing firm-specific earnings forecasts from securities analysts to control for expected future profits. The forecasts are compiled by I/B/E/S International Inc., a private data vendor with extensive ties to the analyst community. Our approach sidesteps the difficult problem of selecting a specific forecasting model for each firm. The professional analysts who track these companies do that for a living, and their expectations are observable. While many firms certainly possess better information about their future prospects than analysts, considerable research suggests that the analysts' forecasts significantly outperform time-series forecasts of firm earnings and contain more information about fundamentals than other variables. Hence, analysts' forecasts likely represent a significant advance over the simple proxies for expected fundamentals used in past studies.

Since expectations of future fundamentals are observable before investment takes place, we first estimate a linear rational expectations model using OLS. We then estimate the same model using GMM for robustness. In this framework, the coefficient estimate on our liquidity variable measures its contribution after controlling for expected future conditions, and it should be zero if there are no binding financial constraints. Because the assumptions required to derive a linear model are quite restrictive, we next explore whether internal funds influence investment with a variety of semiparametric estimators that accommodate a general nonlinear relationship between investment and fundamentals.

We find that analysts' earnings expectations are very important determinants of investment. In the simple linear model using OLS with expected earnings to approximate marginal q or using GMM with lagged expected earnings as instruments, internal funds provide no additional explanatory power. The coefficient estimates on both our liquidity variables are usually near zero and statistically insignificant. We find similar results for the firms that previous studies have argued are constrained by internal funds: firms that do not pay dividends, and firms without bond ratings. Our semiparametric regressions indicate that investment responds nonlinearly to expected fundamentals. The investment response is very large for small values of our proxy to marginal q but modest in the remainder of the distribution. The semi- and non-parametric results are also inconsistent with the view that binding liquidity constraints affect investment. Indeed, regardless of the semiparametric method, the coefficient estimates on both liquidity variables are statistically insignificant from zero. Since both the highly parameterized and the semiparametric estimators reveal no evidence of liquidity effects — at least as they have been traditionally interpreted — we conclude that analysts' expectations provide crucial information about future fundamentals not contained in the instrumental variables that have been used in previous studies.

In work related to ours, Kaplan and Zingales (1997) and Schnure (1997) reassess prior research that claims to find evidence of liquidity constraints on investment. These two papers take a closer look at the firms alleged to be financially constrained in Fazzari, Hubbard, and Petersen (1988) and Lamont (1997) and conclude that most of them were not. In particular, these recent studies show that high-sensitivities of investment to cash flow cannot be interpreted as evidence of financial constrains. Our results complement Kaplan and Zingales (1997) and Schnure (1997) by explaining why previous studies could have found a link between cash flow and investment for firms that actually face no constraints — namely, that cash flow proxies for neoclassical fundamentals when other measures of fundamentals are noisy.

In the next section, we present a basic empirical investment model, review how it has been estimated, and discuss how analysts' earnings forecasts can be used to estimate it. We show that previous tests have been a restricted form of the partially-linear model, and discuss how to perform more general tests that require less tight parameterizations of the null model using semiparametric methods. In section 3, we discuss the data. In section 4, we present our results. The final section concludes and suggests directions for future research.

2 Basic Investment Model

2.1 The Model

The model we use is a standard one in the investment literature. The firm maximizes the expected present discounted value of future profits at time t:[2]

$$\mathrm{E}_t\left\{\sum_{s=t}^{\infty}\left(\prod_{j=t}^{s}\beta_j\right)\Big[\Pi(K_{s-1}) - C(I_s, K_{s-1}, \omega_s) - I_s\Big]\right\}, \tag{1}$$

where E_t is the expectations operator conditional on the set of information available at the beginning of period t, Ω_{t-1}; $\beta_s = (1+\rho_s)^{-1}$ is the time s discount factor; I_s is gross investment; K_{s-1} is the capital stock at the beginning of period s; $\Pi(K_{s-1})$ represents the revenue function; $C(I_s, K_{s-1}, \omega_s)$ is the adjustment cost function, which includes the productivity shock ω_s as an argument.[3] We assume that capital is the only quasi-fixed factor and that variable factors have been maximized out of Π. For convenience in presenting the model, we also assume that the price of investment relative to output is unity and that there are no taxes. In our empirical work we incorporate data on the after-tax price of investment to construct tax-adjusted Q. The adjustment cost technology and the productivity shock are discussed in detail below.

Firms maximize (1) by choosing I_t for all periods t, subject to the usual constraint on their capital stock:

$$K_t = (1-\delta)K_{t-1} + I_t,$$

where δ is the rate of economic depreciation.

The first-order condition for this constrained maximization is:

$$1 + \frac{\partial C(I_t, K_{t-1})}{\partial I_t} = q_t. \tag{2}$$

[2]The firm index i is suppressed where notationally convenient.

[3]The assumption that the adjustment cost function is additively separable from the revenue function is made for consistency with the literature. It is not necessary for the semiparametric estimators we present below.

This equation shows that the full cost of acquiring and installing a unit of capital must equal q, the shadow price of capital. The shadow price evolves according to:

$$\mathrm{E}_t\beta_{t+1}\left[\frac{\partial\Pi}{\partial K_t}-\frac{\partial C}{\partial K_t}\right]=q_t-(1-\delta)\mathrm{E}_t\left[\beta_{t+1}q_{t+1}\right]. \tag{3}$$

Solving equation (3) for its stationary solution, we obtain the following expression for marginal q:

$$q_t=\mathrm{E}_t\sum_{s=t}^{\infty}\left[\prod_{j=t}^{s}\beta_{j+1}(1-\delta)^{s-t}\right]\left(\frac{\partial\Pi}{\partial K_s}-\frac{\partial C}{\partial K_s}\right). \tag{4}$$

Equation (4) states that marginal q equals the present discounted value of the stream of net revenue generated by the marginal unit of undepreciated capital.

Given an explicit form for the adjustment cost function, equation (2) can be manipulated to express the investment-capital ratio in terms of marginal q. The adjustment cost technology we choose is a standard one in the investment literature (adding the firm index i):

$$C(I_{it},K_{i,t-1})=\frac{\alpha}{2}\left(\frac{I_{it}}{K_{i,t-1}}-\delta-\omega_{it}\right)^2K_{i,t-1}. \tag{5}$$

In this function, adjustment costs are convex in net investment.[4] If we substitute $\frac{\partial C(I_t,K_{t-1})}{\partial I_t}$ into equation (2) and rearrange terms, we obtain a simple equation linking investment to marginal q:

$$\frac{I_{it}}{K_{i,t-1}}=\delta+\frac{1}{\alpha}(q_{it}-1)+\omega_{it}. \tag{6}$$

We assume that the productivity shock ω_{it} is the sum of three mean-zero components:

$$\omega_{it}=\nu_i+\upsilon_t+\epsilon_{it}, \tag{7}$$

[4]Alternatively, adjustment costs could be modeled as a convex function of gross investment. While the distinction between adjustment costs in net or gross investment is important in some applications, it is not in our study.

where ν_i accounts for unobserved firm-specific heterogeneity, assumed to be constant over time; υ_t captures cyclical factors that have a common effect on all firms; and the final component, ϵ_{it}, is a stochastic disturbance to the firm's production process. We assume ϵ_{it} is independently and identically distributed (iid) across firms, but can be serially correlated over time for each firm.[5]

Equation (6) is a standard empirical formulation of the neoclassical investment model under the null of perfect capital markets.[6] Numerous studies have used this equation to test the null against the alternative in which financial factors affect investment. The usual procedure is to augment equation (6) with a variable — typically, cash flow — that contains information about a firm's financial position. However, this approach yields valid tests only if marginal q is accurately measured. The problem is that measures of internal net worth, like cash flow, signal not only the firm's financial position, but also may be correlated with its expected investment opportunities. If marginal q is mismeasured, the estimated coefficient on cash flow could be positive and statistically significant even if the null model is correct.

Because marginal q is unobservable, this bias toward rejecting the null model afflicts all previous empirical work on investment and financing constraints, at least to some extent. Often, researchers have proxied for marginal q with Tobin's average Q, defined as the ratio of the market value of the firm to the replacement cost of its capital stock (see, e.g., Fazzari, Hubbard, and Petersen 1988; Blundell, Bond, Devereux, and Schiantarelli 1992; Vogt 1994; Chirinko and Schaller 1995). Hayashi (1982) provided the theoretical basis for this substitution, showing that average Q equals marginal q if the firm has a linear homogeneous net revenue function and operates in perfectly competitive markets. These are strong assumptions but this practice is especially problematic given the substantial evidence of excess volatility in stock prices (see, e.g., Shiller 1989). Recognizing this problem, some studies have augmented average Q with additional lagged variables (e.g. the ratio of sales to beginning-of-period capital) to control for investment opportunities. These additional variables, while likely an improvement over the

[5] Alternatively, one can think of ϵ_{it} as a measurement error or optimization error that allows the firm's first-order conditions to be satisfied only in expectation (from the perspective of the econometrician).

[6] There are several other ways to obtain empirical representations of the neoclassical investment model. The most common alternative is based on the Euler equation in (3).

use of average Q by itself, still constitute a far smaller information set than firms actually use to form expectations of returns to investment. Moreover, even if other lagged variables are included as controls in equation (6), the regression technique forces the relationship between lagged variables and future investment returns to be the same across the entire sample (or at least across the subsample chosen); yet, the past may not be equally informative for all firms.[7]

2.2 Estimation: Parametric Model

We use several econometric techniques to test for financial constraints. To implement our tests, we assume that marginal q in equation (4) is some unknown function $\mathfrak{f}$ that can be approximated using beginning-of-period expectations about future cash flows, which we will denote:

$$\mathfrak{f}(\mathbf{z}_{it}) \approx q_{it} - 1, \tag{8}$$

where $\mathbf{z}_{it}$ is a vector of expected future cash flows.[8]

There are a number of different variables that could capture changes in internal net worth. In most of our empirical work we use the ratio of once-lagged net income to beginning-of-period capital, $CF_{i,t-1}$. The logic is straightforward. If firms face binding financial constraints, they will invest all available operating profits, even the part that is uncorrelated with expected future profitability. For comparability with the literature and for robustness we also use an additional measure of liquidity, the ratio of cash flow to beginning-of-period capital, denoted "Compustat" CF_{it}.

Given these assumptions the model we estimate is obtained by substituting equation (8) into (6) and including $CF_{i,t-1}$ (or Compustat CF_{it}) as a regressor:

$$\frac{I_{it}}{K_{i,t-1}} = \delta + \frac{1}{\alpha}\mathfrak{f}(\mathbf{z}_{it}) + \gamma CF_{i,t-1} + \omega_{it}. \tag{9}$$

[7]This point applies also applies to the literature that has used Euler equations to test for financial constraints on investment. Euler equations proxy for future expectations with a potentially large set of variables but still impose a common expectations process across firms (see, e.g., Gilchrist 1990; Himmelberg 1990; Whited 1992; Hubbard and Kashyap 1992; Bond and Meghir 1994; Hubbard, Kashyap, and Whited 1995).

[8]We can assume that the approximation error is part of ϵ_{it}.

As we will discuss in more detail below, the I/B/E/S data contain three variables that can be used to approximate marginal q: One- and two-year-ahead earnings forecasts, and a forecast of long-term earnings growth. For our parametric estimation, we combine these forecasts into a tightly specified formulation for $\mathfrak{f}(z_{it})$, called real Q_{it}. Let ECF_{it} and $ECF_{i,t+1}$ denote the firm's expected net income in periods t and $t+1$, respectively, with each scaled by the capital stock at the beginning of period t, and let $EGROW_i$ denote the firm's expected growth rate of net income in the following periods. All these expectations are formed at the beginning of period t. We calculate the implied level of net income for periods after $t+1$ by growing out $ECF_{i,t+1}$ at the rate of $EGROW_i$. The resulting sequence of net incomes (scaled by the capital stock at the beginning of period t) serves as a proxy for the values of the derivatives in equation (4). We set the constant discount factor in equation (4) to 0.91 (reflecting a 0.10 interest rate), and the depreciation rate to 0.10. For this specification of $\mathfrak{f}$ we rely, as others have, on Hayashi's result linking average Q and marginal q.[9]

This approach is similar to that of Gilchrist and Himmelberg (1995), except that their proxy for $\mathfrak{f}$ is constructed using a linear forcing process in observable firm variables (period $t-2$ and $t-3$ sales and operating income before depreciation) and ours is constructed from earnings forecasts. It is also similar to the methods used by Abel and Blanchard (1986) and Auerbach and Hassett (1992), who constructed a proxy for $\mathfrak{f}$ using approximations to future marginal cash flows and future marginal costs, respectively. All these parameterizations (including ours) present difficulties: they require assumed values for the unobserved discount and depreciation rates applied to expected cash flows, and an assumed functional form of the unknown derivatives in equation (4) $(\partial\Pi/\partial K_t - \partial C/\partial K_t)$. To address these concerns we develop a semiparametric approach in the next subsection.

We present results from this strict parameterization to assess the explanatory power of the earnings forecasts while adhering, in other respects, to the methodology of

[9]Caballero and Leahy (1996) argue that average Q, not marginal q, is the correct measure of fundamentals when there are certain types of fixed costs. While it not possible for us to directly identify fixed costs in our firm-level data, our approach is consistent with their study since we use average Q to approximate marginal q. Our empirical results support their suggestion to interpret the significance of cash flow in investment equations not as a signal of the presence of liquidity constraints, but as a variable that helps capture fundamentals.

previous studies. Specifically, we estimate equation (9) in first-differences using OLS and GMM. The equation is first-differenced to remove the firm-specific error component, ν_i, and time dummies are introduced as regressors for υ_t in each period. The GMM estimator accommodates conditional heteroskedasticity of unknown form in the stochastic error-component ϵ_{it}. When the error terms are serially uncorrelated, lagged endogenous variables are valid instruments. However, first differencing introduces a first-order moving average error that necessitates using instruments dated at $t-2$ and before. If the model is misspecified the error terms may display higher-order serial correlation, in which case even instruments dated at $t-2$ and before may be invalid. Hence it is important to test for the presence of this higher-order serial correlation. In our empirical results we report the Sargan statistic, which is a test of the joint null hypothesis that the model is correctly specified and that the instruments are valid. (for further theoretical details see, e.g., Arellano and Bond 1991; Blundell, Bond, Devereux, and Schiantarelli 1992).[10] Unfortunately, it is not possible to test either hypothesis separately. So considerable caution should be exercised in interpreting why the null is rejected — the instruments may be invalid due to serially correlation or, more seriously, the model may be misspecified, or both.

We also present OLS and GMM estimates of a more traditional model that uses tax-adjusted Q as the control for fundamentals. These provide a direct comparison to previous literature. The GMM estimates, which use the individual I/B/E/S variables as instruments for tax-adjusted Q, help assess whether the assumptions used to construct real Q bias the results. Concerns about potential bias will be allayed if these GMM results using tax-adjusted Q are qualitatively similar to those using real Q.

2.3 Estimation: Semiparametric Model

Most studies make parametric assumptions about the revenue and adjustment cost functions to estimate the relationship between investment, fundamentals, and liquidity variables. However, such assumptions are unnecessary. In particular, if we assume that the function for marginal adjustment costs is invertible so that $(I_{it}/K_{i,t-1})$ can be

[10]Formally, the Sargan statistic is a test that the overidentifying restrictions are asymptotically distributed $\chi^2_{(n-p)}$, where n is the number of instruments and p is the number of parameters.

expressed as some unknown function $\mathfrak{G}$, we can write equation (9) more generally:

$$\frac{I_{it}}{K_{i,t-1}} = \mathfrak{G}(q_{it}, \delta, \omega_{it}) + \gamma CF_{i,t-1}. \tag{10}$$

Equation (10) is a partially-linear model that can be estimated using semiparametric techniques. When liquidity effects are not binding, the coefficient estimate on $CF_{i,t-1}$ will equal zero and equation (10).

To implement the semiparametric estimator, we must specify how the productivity shock ω_{it} enters $\mathfrak{G}$. We take two different approaches. First, we assume that the error component ϵ_{it} is additively separable from $\mathfrak{G}$ but that the firm error ν_i and time error υ_t components are not. This assumption reflects the way in which analysts form forecasts of future earnings. Consider the firm fixed effect. It arises from the presence of unobserved heterogeneity that is approximately constant over time — for example, Bill Gates' managerial skill in running Microsoft. When the analysts forecast Microsoft's future earnings they take into account this fixed effect. A similar argument can be made to motivate the presence of time effects in analysts' forecasts — analysts take cyclical effects into consideration when making forecasts. Thus the firm and time effects are likely to be impounded in the triple $(ECF_{it}, ECF_{i,t+1}, EGROW_i)$, which is used to nonparametrically approximate $\mathfrak{G}$. If this is the case, ν_i and υ_t cannot be separately identified, but are controlled for in using the triple to approximate $\mathfrak{G}$. The remaining error component ϵ_{it} can be interpreted as a productivity shock that is not reflected in the analysts' forecasts. We call this the semiparametric levels model.

Alternatively, we assume that the error components are additively separable from $\mathfrak{G}$. This is a more familiar error-components formulation but is a special case of the semiparametric levels estimator. We examine this special case since we cannot be absolutely sure that the analysts' earnings forecasts incorporate the firm- and time-effects. We first difference this formulation to remove the firm-effect and use year dummy variables as regressors for ν_t in each period.[11] We call this the semiparametric first-differences model.

[11] We allowed for interactions between the year dummies and the triple but found that they didn't significantly improve the model fit.

We estimate the semiparametric levels model by projecting $(I_{it}/K_{i,t-1})$ on $CF_{i,t-1}$ and a nonparametric approximation to $\mathfrak{G}$ in the triple $(ECF_{it}, ECF_{i,t+1}, EGROW_i)$. We estimate the semiparametric model in first-differences by projecting $\Delta(I_{it}/K_{i,t-1})$ on $\Delta CF_{i,t-1}$, year dummy variables, and the nonparametric approximation to $\mathfrak{G}$ in first differences of the triple. We use several different nonparametric methods to gauge the sensitivity of our results to the quality of the nonparametric fit. These methods include polynomial series, projection pursuit, and multivariate adaptive regression splines (MARS).

The econometric properties of the partially-linear model have been the focus of a number of recent studies. Under weak regularity conditions the estimate of γ in equation (10) is $\sqrt{N}$-consistent when $\mathfrak{G}$ is estimated using the product kernel, series, or splines (see, e.g., Andrews 1991; Robinson 1988; Li and Stengos 1996; Newey 1997; Newey 1995). We also estimate γ using projection pursuit and MARS (which is a more general spline method) for additional robustness, even though to our knowledge they have yet to be proven $\sqrt{N}$-consistent.[12]

Our semiparametric approaches do not account for the possible correlation of ϵ_{it} $(\Delta\epsilon_{it})$ with $CF_{i,t-1}$ $(\Delta CF_{i,t-1})$. We are confident that our results will be unaffected since it is difficult to imagine what type of productivity shock would bias downward the coefficient estimate on $CF_{i,t-1}$, as higher productivity, conditional on fundamentals, is usually associated with higher net income or cash flow. In other words, if ϵ_{it} is correlated with $CF_{i,t-1}$ it would likely bias upward the coefficient estimate on $CF_{i,t-1}$. Nevertheless, the parametric GMM estimates are consistent in this case, so these results can be used to gauge whether this is a problem.

In summary, our empirical approach proceeds in two steps. First, we evaluate whether fundamentals help explain investment behavior using real Q as an explanatory variable and analysts' earnings forecasts as instrumental variables. In this tightly parameterized framework much of the evidence for capital market imperfections can then be reevaluated. In particular, it is possible to reassess whether variables that capture changes in internal net worth are correlated with investment spending controlling for

[12]It is likely, however, that all of the estimators of γ have the same limiting distribution. Research on properties of semiparametric estimators is progressing rapidly enough that results may soon be available on the more computationally efficient nonparametric methods like projection pursuit and MARS.

expected earnings. Second, we investigate the effect of relaxing these tight parametric restrictions.

3 Data

We estimate the model using a firm-level panel dataset constructed from two primary sources. The firm data on investment, the capital stock, tax-adjusted Q, cash flow, and the variables used to split the sample are from Compustat, while the data on actual and expected earnings are from I/B/E/S International Inc. We first briefly describe the Compustat data and then describe in greater detail the I/B/E/S data. To be included in our sample for a given year, a firm must have complete data from both sources.

3.1 Compustat Dataset

The Compustat dataset is an unbalanced panel of firms from the industrial, full-coverage, and research files. The variables we use are defined as follows. The replacement value of the capital stock is calculated using the standard perpetual inventory method with the initial observation set equal to the book value of the firm's first reported net stock of property, plant, and equipment (data item 8) and a firm-level rate of economic depreciation constructed using the method in Cummins et al. (1994). Gross investment is defined as the direct measure of capital expenditures in Compustat (data item 30).[13] The investment variable is divided by the beginning-of-period replacement value of the capital stock. Although I/B/E/S provides our principal measure of internally generated funds, we also explore the effect of using the Compustat cash flow variable employed in most studies -- namely, the sum of net income (data item 18) and depreciation (data item 14). Both liquidity variables are divided by the beginning-of-period replacement value of the capital stock. The construction of tax-adjusted Q is discussed in detail in the appendix. The capital stock and investment variables are deflated by the nonresidental fixed investment deflator and the liquidity variables are deflated by the GDP

[13] An alternative definition of gross investment is the sum of depreciation (data item 14) and the change in the net stock of property, plant and equipment. We use the capital expenditures variable to maintain comparability to previous studies.

deflator. These price deflators are obtained from Citibase. We use Compustat data on the firms' S&P bond rating and dividend payouts to split the sample, isolating those firms that may *a priori* face financial constraints.

We delete observations when (1) the ratio of investment to beginning-of-period capital is greater than unity or less than zero; (2) tax-adjusted Q_{it} or real Q_{it} are greater than 10; or (3) the ratio of Compustat cash flow to the beginning-of-period capital stock is greater than 3 or less than zero.[14] These types of rules are common in the literature and we employ them to maintain comparability to previous studies; in section 4.6 we discuss how our results are affected when we use alternative cut-offs. The first cut-off is intended to eliminate observations that reflect especially large mergers, extraordinary firm shocks, or Compustat coding errors. The second is intended to remove firms for which fundamentals may be more mismeasured. The final rule increases the power of the test for liquidity constraints, since firms with negative cash flow would be expected to have a weaker link between cash flow and investment given that our investment variable does not include asset sales; in fact, the high coefficients on $CF_{i,t-1}$ that we present in Table 2 — which reproduce the basic results of many previous studies — are lowered substantially if we do not delete the negative cash flow observations.

3.2 I/B/E/S Dataset

We employ data on expected and actual earnings from I/B/E/S International Inc., a private company that has been collecting earnings forecasts from securities analysts since 1971. I/B/E/S markets the data mainly to institutional clients, but also makes extensive historical data available to academic researchers.

To be included in the I/B/E/S database, a company must be actively followed by a securities analyst, who agrees to provide I/B/E/S with timely earnings estimates. According to I/B/E/S, an analyst actively follows a company if he or she produces research reports on the company, speaks to company management, and issues regular earnings

[14]The first exclusion rule deletes about 10 percent of the potential sample, the second about 25 percent, and the third about 20 percent. Taken together the rules delete somewhat less than 40 percent of the potential sample.

forecasts. These criteria ensure that I/B/E/S data come from reasonably well-informed sources.

Both the I/B/E/S earnings forecasts and their reported actual earnings refer to net income from continuing operations as defined by the consensus of securities analysts following the firm. Typically, this consensus measure removes from earnings a wider range of non-cash charges than the "extraordinary items" reported on firms' financial statements. In our empirical work, we use I/B/E/S data on actual earnings as our primary measure of liquidity.[15]

For each company in the database, I/B/E/S asks analysts to provide forecasts of earnings per share over the next four quarters and each of the next five years. We focus on the annual forecasts to match the frequency of our Compustat data. In practice, few analysts provide annual forecasts beyond two years ahead, precluding our use of more forward-looking estimates. Fortunately, we can fill this void. I/B/E/S obtains a separate forecast of the average annual growth of the firm's net income over the next three to five years — the so-called "long-term growth forecast" which we denoted above as $EGROW_i$. When calculating their forecasts of long-term growth, I/B/E/S instructs analysts to ignore the current state of the business cycle and to project, instead, the expected trend growth of the company's earnings. Thus, the long-term growth forecast should contain information not in the one-year-ahead and two-year-ahead forecasts, which necessarily will be affected by current conditions. And for companies that make investment decisions based on the expected long-term returns to capital — in accord with the neoclassical model — the long-term growth forecast should be the more important determinant of investment.

We abstract from any heterogeneity in analyst expectations for a given firm-year by using the mean across analysts for each earnings measure (which I/B/E/S terms the "consensus" estimate).[16] We multiply the one-year-ahead and two-year-ahead forecasts

[15]After extensive study of the I/B/E/S database, Philbrick and Ricks (1991) expressed concerns about the reliability of the quarterly data on actual earnings. In particular, they discovered that the data were sometimes recorded in the wrong quarter and found it suspicious that I/B/E/S reported no instances of negative earnings. We raised these concerns with officials at I/B/E/S, who acknowledged earlier problems with the data. They have since undertaken an extensive effort to correct errors in the quarterly and annual data on actual earnings and assure us that the data are now clean.

[16]In future research we plan to examine higher moments of the distribution of analysts' forecasts in our estimators.

of earnings per share by the number of shares outstanding to yield forecasts of future earnings levels. As noted above, we generate the variables ECF_{it} and $ECF_{i,t+1}$ by scaling these forecasts of net income in periods t and $t+1$ by the beginning-of-period capital stock from Compustat.

The one-year-ahead and two-year-ahead forecasts are available from 1976 but the long-term growth forecasts were not collected until 1981, which constrains the starting point of our sample. The data coverage improves gradually over time, with the Compustat universe largely covered by 1994. At the end date of our sample, December 1995, the I/B/E/S database included about 5,000 US corporations that were actively followed by securities analysts, plus nearly as many defunct companies that were previously covered.

An important issue concerns the dating of the I/B/E/S earnings forecasts. Shortly after the end of a firm's fiscal year, securities analysts send I/B/E/S an initial forecast of earnings for the fiscal year that has just begun and for the next fiscal year. These are what we have called the one-year-ahead and two-year-ahead forecasts. As the fiscal year progresses, analysts process new information and file revised forecasts with I/B/E/S, yielding a sequence of one-year-ahead and two-year-ahead consensus forecasts for the firm. Similarly, I/B/E/S posts a sequence of consensus long-term growth forecasts over the fiscal year. We use the first forecast in each sequence.[17] By relating investment in year t to earnings forecasts issued at the beginning of the year, we reduce the risk of using more information than the firm actually has when it determines investment spending for the year. With time-to-build lags, however, investment in year t may have been determined in large part or completely by information available before the start of year t. In this case, the GMM results we present are consistent as long as the time-to-build lags do not exceed two years since we use an instrument set containing earnings forecasts formed at the beginning of year $t-2$ and earlier.

Our empirical work hinges on the assumption that I/B/E/S earnings forecasts are better measures of the expected returns to investment than those used in previous studies. The empirical results in the next section attest to this, but here we provide

[17]The first forecast is within 2 months of the beginning of the fiscal year for 75 percent of our sample and within 3 months for 97 percent of our sample.

some direct evidence with forecasting "horse races." We compare the predictive power of I/B/E/S earnings forecasts and lagged values of the average return to capital — defined as operating income before depreciation (Compustat data item 13), $OIBD_{it}$ — for forecasting future realizations of the average return to capital. In our full sample, an OLS regression in first differences of current year $OIBD_{it}$ on its lag and the lagged I/B/E/S one-year-ahead earnings forecast, ECF_{it}, yields the following results:

$$OIBD_{it} = \underset{(0.009)}{-\ 0.029} + \underset{(0.041)}{0.002}\ OIBD_{i,t-1} + \underset{(0.054)}{1.26}\ ECF_{it}.$$

Thus, conditional on the lagged value of the one-year-ahead earnings forecast, lagged $OIBD$ fails to provide any additional explanatory power. We also estimate an OLS regression in first differences using the present discounted value of future operating incomes before depreciation, FQ_{it}, constructed like real Q_{it}. Regressing this variable on lagged operating income before depreciation and the I/B/E/S one-year-ahead, two-year-ahead, and long-term growth forecasts yields:

$$FQ_{it} = \underset{(0.032)}{-\ 0.022} - \underset{(0.157)}{0.166}\ OIBD_{i,t-1} + \underset{(0.258)}{1.44}\ ECF_{it} + \underset{(0.197)}{0.449}\ ECF_{i,t+1} + \underset{(0.434)}{2.68}\ EGROW_{t}.$$

These results also show that lagged $OIBD$ does not provide any additional explanatory power.[18]

A large literature on the properties of earnings expectations supports the idea that analysts' forecasts approximate the future returns to capital better than econometric forecasts.[19] In particular, many studies have found that analysts predict future earnings significantly better than time-series forecasts using accounting data (see, e.g., O'Brien 1988; Brown, Griffin, Hagerman, and Zmijewski 1987; Fried and Givoly 1982). The reason why is that analysts' incorporate more than just historical accounting data into their forecasts. In addition, as described above, analysts' also remove from their

[18]The OLS regressions in first differences are complicated by the first-order moving average error and the presence of any correlation between the regressors and the disturbance. However, we obtained similar results when we estimated the same regressions with GMM using lagged regressors as instruments. We focus only on the results in first differences since the levels estimates of a dynamic model are inconsistent when there are fixed effects.

[19]For surveys of the literature see Coggin (1990); Brown (1993, 1996a); Givoly and Lakonishok (1984); for an annotated bibliography covering more than 400 articles on earnings expectations see Brown (1996b).

forecasts a variety of immaterial items.[20] Nevertheless, analysts' forecasts may not contain all available information. While some studies have failed to reject rationality (see, e.g., Keane and Runkle 1994), others have found that analysts' forecast errors are predictable (see, e.g., Brown, Han, McKeon, and Quinn 1996). For our purposes, full rationality is not crucial; we only require that the I/B/E/S forecasts dominate the proxies for fundamentals used in previous studies.

4 Empirical Results

This section summarizes our results in six subsections. The first subsection discusses our sample. The next provides our parametric estimation results. The third and fourth subsections present our semiparametric results and a graphical exposition of them. The fifth subsection briefly discusses the aggregate implications of our results. The final subsection provides sensitivity analysis.

4.1 Sample Statistics

In table 1 we provide the means, medians, and standard deviations from 1984 to 1995 for the primary variables in our dataset. The first column contains the ratio of investment to beginning-of-period capital. Its mean and median are always greater than 0.20, showing that the sample contains many firms regularly making large investments. Also, given the standard deviation of 0.17 for the full sample, our firms span a wide range of investment activity. The second column contains our linear approximation to marginal q based on the I/B/E/S one-year-ahead, two-year-ahead, and long-term growth forecasts, which we have called real Q_t. The third column contains tax-adjusted Q_t, which has a mean and median that are usually at least twice those of real Q_t, presumably resulting from the omission of the returns to debt holders in real Q_t. Similarly, the standard deviation of tax-adjusted Q is always greater than that of real Q_t. The final

[20]Empirical research in accounting strongly supports the claim that earnings-based measures provide more information about firms' future performance than measures related to cash flow, such as *OIBD* and the sum of net income and depreciation (see, e.g., Ball and Brown 1968; Beaver and Dukes 1972; Beaver, Griffin, and Landsman 1982). In fact, this is a fundamental tenet of accounting (see, e.g., Financial Accounting Standards Board 1978, p. ix, which says that financial reporting should focus on earnings as opposed to cash receipts and payments).

two columns contain our two measures of liquidity, I/B/E/S net income and Compustat cash flow. The Compustat measure includes depreciation, so its mean, median, and standard deviation are always greater than the I/B/E/S measure.

Our sample has less than half of the total number of observations of the entire Compustat universe. However, it does make up between 70 and 80 percent of the aggregate sales, capital stock, and investment of the Compustat universe in each year. This means that our sample is skewed away from the small firms thought to be constrained by internal funds. While we still have an ample number of firms that do not pay dividends or have a bond rating, a possible concern is that our sample seriously underweights the liquidity constrained firms in the Compustat universe. We plan to address this important question directly in future research, but we can gauge in a simple way whether the omitted firms play an important role in explaining aggregate investment.

We construct the aggregate ratios of investment to beginning-of-period capital for our sample and the entire Compustat universe for each year. We then regress the aggregate Compustat investment-to-capital ratio on our sample's aggregate investment-to-capital ratio. The R^2 from this regression is the total variation in the Compustat ratio explained by the ratio in our sample. This regression yields an estimated slope coefficient of 0.876 with a standard error of 0.078 and an $R^2 = 0.927$. In first differences the same regression yields a coefficient estimate of 1.000 with a standard error of 0.120 and an $R^2 = 0.886$. In both regressions the intercepts are statistically insignificant from zero. The nearly one-for-one movement in these ratios means we can learn about the investment behavior of the Compustat universe from our smaller sample, even if, for the sake of argument, all the Compustat firms outside our sample are liquidity constrained.

4.2 Parametric Estimation Results

Table 2 presents OLS estimates of the first difference of equation (9) using two different variables to control for fundamentals: beginning-of-period tax-adjusted Q_{it}, constructed using Compustat data, and real Q_{it}, constructed using I/B/E/S data. For each column, the dependent variable is the first difference of the ratio of investment to beginning-of-period capital. Column 1 reports a regression of this variable on the first differences of beginning-of-period tax-adjusted Q_{it} and the ratio of lagged net income to beginning-of-period capital, $CF_{i,t-1}$. This regression reproduces the qualitative results of most previous studies of investment and internal funds. As is typically found, the coefficient estimate on tax-adjusted Q_{it} is positive and statistically significant, but very close to zero, while the coefficient on $CF_{i,t-1}$ is large and highly significant. This pattern holds in column 3 for the subsample of firms without bond ratings and in column 5 for the subsample of firms that pay no dividends — groups found to be "constrained" in many studies. Columns 7, 9, and 11 present similar results for manufacturing firms and the subsamples.[21]

The equation we estimate in column 2 is identical to that in column 1, except that we replace beginning-of-period tax-adjusted Q_{it} with real Q_{it}. As noted above, we construct real Q_{it} according to equation (4) with I/B/E/S earnings forecasts, discounting these nominal flows with a 0.10 discount rate and 0.10 depreciation rate. The assumptions used to construct real Q_{it} make the structural interpretation of its coefficient estimate extremely suspect because, by construction, we do not allow for cross-sectional variation in the discount and depreciation rates. This must be important because firms in our sample with very large expected growth rates have finite stock-market values. To keep the PDV calculation from generating outliers — given this discounting assumption — we stopped the summation after 10 years.[22]

As shown in column 2, the coefficient estimate on real Q_{it} is highly significant and about ten times larger than the coefficient estimate on tax-adjusted Q_{it}. Even more striking, the coefficient estimate on $CF_{i,t-1}$ is small and statistically insignificant. This result, however, need not rule out liquidity constraints for a subsample of firms that may face some kind of information problem. Depending on the relative importance of constrained and unconstrained firms, one could find statistically insignificant effects of liquidity on investment in the full sample. However, as can be seen in the subsample regressions in columns 4, 6, 10 and 12, the coefficient estimates on $CF_{i,t-1}$ are never

[21]We should note that there is disagreement in the literature over whether firms that do not pay dividends are really constrained: Gilchrist and Himmelberg (1995) find that they appear unconstrained, whereas Fazzari, Hubbard, and Petersen (1988) find the opposite.

[22]Changes in the cutoff date did not qualitatively affect the results. Abel and Blanchard (1986) and Gilchrist and Himmelberg (1995) did not discuss their method for handling this potential problem, so this step may or may not introduce a methodological inconsistency with past studies.

statistically significant from zero and in the two "no dividend" subsamples the point estimate is even negative.

The estimates in table 2 tell a story that differs sharply from that in previous research. When we control for fundamentals with tax-adjusted Q we find a large "liquidity" effect. But, when we control for fundamentals using a simple linear function of analysts' expectations, which arguably contain less noisy information concerning firms' true neoclassical fundamentals, we find no liquidity effect whatsoever. In other words, holding constant neoclassical fundamentals, if you give a firm \$1 they don't invest it.

There are two primary sources of bias that could affect the OLS results. First, differencing introduces an MA(1) error term, which may cause the explanatory variables to be correlated with the resulting error term. Second, as discussed above, the construction of real Q_{it} relies on several restrictive assumptions. If internal funds are unimportant in table 2 because analysts' forecasts truly measure fundamentals better than has been done in the past — and not simply because of the restrictive assumptions behind real Q_{it} — then we should obtain similar results when we use the analysts' forecasts as instruments for tax-adjusted Q_{it}. For both reasons we now turn to GMM estimation of the two equations.

Table 3 provides GMM estimates of the investment equations in first differences using both tax-adjusted Q_{it} and real Q_{it}. The odd-numbered columns contain our estimates using tax-adjusted Q_{it}. The instrumental variables are the period $t-2$ and $t-3$ ratios of investment to beginning-of-period capital; the ratios of the analysts' forecasts of one-year-ahead and two-year-ahead earnings to beginning-of-period capital; and the long-term growth forecasts. There are two major differences between these results and those in table 2. First, the coefficient estimates on tax-adjusted Q_{it} are substantially larger. For example, the estimate in column 1 of table 3 is more than twenty times larger than that in column 1 of table 2 (0.188 compared to 0.008). This increase in size suggests that tax-adjusted Q is a very noisy indicator of fundamentals; only the part of Q correlated with analysts' earnings expectations has a sizable effect on investment spending. Second, the estimated coefficient on $CF_{i,t-1}$ is now insignificant, in contrast to the highly significant coefficients shown in table 2 when we used beginning-of-period tax-adjusted Q_{it} directly as a measure of fundamentals. This contrast implies that internal funds were important in table 2 because tax-adjusted Q is a poor measure of fundamentals. The even numbered columns present the estimates in which we use the same instruments for real Q_{it}.[23] The coefficient estimates on $CF_{i,t-1}$ are insignificant, just as they were in table 2 when we used real Q_{it} as a direct control for fundamentals. Hence, the "disappearance" of the coefficient estimate on $CF_{i,t-1}$ has nothing to do with the rather strong assumptions needed to construct real Q_{it}. Finally, in some cases the Sargan statistic rejects the overidentifying restrictions of the models, suggesting that nonlinearities may well be important, a point we return to below.

The earnings forecasts we use to construct real Q_{it} and as instruments may impound not only neoclassical fundamentals but also the effects of any current or expected liquidity constraints. This fact, however, does not vitiate our testing procedure as long as our liquidity variable has some variation that is independent of fundamentals.[24] If a firm were liquidity constrained today, investment should respond to a cash windfall. But in our regressions we find no such response to cash inflows that are uncorrelated with expected future profits. This lack of response implies that the firms in our sample do not face *currently binding* liquidity constraints.

4.3 Semiparametric Estimation Results

The results so far have used simple linear methods to approximate marginal q. Given that a growing body of research suggests that this may be a poor specification of the null model, it is important to explore whether the liquidity results change when we allow for more general nonlinear relationships between fundamentals and investment. In table 4 we address this question and in the next subsection we further characterize the nature of the nonlinearities using only nonparametric methods.

[23]In these estimates we use all the columns of the optimal instrument matrix containing instruments dated $t-2$ and $t-3$.

[24]Obviously, the power to detect liquidity constraints diminishes as the correlation between fundamentals and the liquidity variable increases. In our data, however, regressions of either measure of fundamentals — real Q_{it} or tax-adjusted Q_{it} — on either of our two liquidity variables never yield an R^2 greater than 0.75.

Table 4 presents our estimates of the coefficient on $CF_{i,t-1}$ in the semiparametric levels and first-differences models using a variety of nonparametric methods to approximate marginal q. Each entry in table 4 is the result of a separate semiparametric regression. For example, the value of 0.000 in the first cell of the table is the coefficient estimate on $CF_{i,t-1}$ when we use a third-order (orthogonal) polynomial series expansion to approximate marginal q in the semiparametric levels model. We provide estimates using several different nonparametric approximations to marginal q to explore the sensitivity of our results to choice of technique. Since we use three I/B/E/S variables to approximate marginal q, more familiar nonparametric methods such as the product kernel require curve fitting in a four-dimensional space. Because of this they require the number of observations to increase exponentially with the number of explanatory variables, so they suffer a "curse of dimensionality". The last two nonparametric methods we present in table 4 are designed to ameliorate this problem.

The results accord with those in the previous tables, providing further evidence against the presence of liquidity effects. When marginal q is controlled for with nonparametric functions of I/B/E/S earnings forecasts, the residual effect of liquidity is indistinguishable from zero. This is true regardless of the method used, and even for those subsamples that have been dubbed *a priori* constrained by past researchers.

4.4 Graphical Presentation of Results

The previous subsections presented a number of tests that found no role for liquidity effects in our investment equations. In this subsection, we present scatterplots and kernel "smooths" (i.e., nonparametric regression fits) that visually represent the results in the previous subsection. They provide the intuition for why liquidity variables were found to be so important by previous researchers — namely, because measures of internal funds are highly correlated with with future fundamentals. The nonparametric analysis clearly indicates that the positive correlation between investment and liquidity goes to zero once one controls for fundamentals using real Q_{it} and illustrates the magnitude of the nonlinearities present in the data.

Figure 1 plots the full-sample relationship between investment and lagged net income — both relative to beginning-of-period capital — without performing any controls for future fundamentals. Since the coefficient estimates on tax-adjusted Q in most studies is quite close to zero, this scatterplot is roughly representative of the results in the literature (e.g., column 1 of table 2). The curve drawn is a normal kernel smooth through the data, with the bandwidth set by cross-validation. The plot and smooth clearly indicate positive correlation between these two variables. The function is modestly concave, but the nonlinearity in the relationship is not acute.

Figure 2 is a scatter plot of lagged net income from figure 1 and real Q_{it}. The curve through the data is again a normal kernel smooth, with the bandwidth set by cross-validation. The two variables are positively correlated, with the relationship appearing nearly linear. Since the null neoclassical model suggests that real Q_{it} should be correlated with investment and that $CF_{i,t-1}$ should not, this figure is something of an indictment of the interpretation of any liquidity effect from figure 1.[25] It may be that the liquidity variable there acts as a proxy for fundamentals.

Figure 3 presents a scatter plot of the residuals of investment and lagged net income from nonparametric regressions of each (using normal kernel estimators) on real Q_{it} (i.e. the component of each variable that is orthogonal to real Q_{it}). Once again, a cross-validated normal kernel smooth is fit through the scatterplot. The data indicate that there is no positive correlation between liquidity and investment. Indeed, the distribution of data points is nearly spherical. Apparently, studies find that cash flow is highly positively correlated with investment because it is highly correlated with fundamentals.

Figure 4 is a scatterplot and kernel smooth representing the relationship between investment and real Q_{it}. The two are highly positively correlated, and the relationship appears to be nonlinear. The concavity in the graph is consistent with the results in Abel and Eberly (1996) and Barnett and Sakellaris (1995). Investment advances almost one-for-one with values of real Q_{it} below unity, but investment does not appear to be as responsive to real Q_{it} when Q is very high. This may reflect the fact that adjustment costs are highly nonlinear, or it may simply be that the assumptions we used to construct real Q_{it} introduce significant measurement error for higher values of Q, since,

[25] The corresponding figure using Compustat cash flow is similar.

for example, firms with high projected growth rates should have their cash flows discounted at some rate higher than 0.10. We leave the analysis of whether the nonlinearity reflects measurement error or nonconvex adjustment costs to future research.

4.5 Aggregate Implications

As noted in the introduction, an early motivation of the liquidity literature was the observation that the aggregate time-series correlations between investment and neoclassical fundamentals appeared negligible. Since one goal of investment models is to guide macroeconomic policy, this shortcoming has serious consequences. Figure 5, as a case-in-point, plots the relationship between aggregate I_t/K_{t-1} and Tobin's Q_t in levels and first differences from 1984 through 1995. The measures of investment and capital stock of equipment and structures are taken from aggregate BEA data, and the measure of Q_t is constructed using flow-of-funds data from the Federal Reserve Board. Clearly, the relationship between these series is not consistent with neoclassical theory. Both the levels and the first-differences diverge significantly from one another, and the correlation between the first differences is actually negative.

Given the robust finding in our micro data that real Q_{it} helps predict investment, we investigate whether aggregated real Q_t better predicts the time-series fluctuations of investment. Figure 6 plots the BEA's investment-capital ratio against an aggregate real Q_t variable we constructed from the I/B/E/S and Compustat data by taking the capital-stock weighted average of the firm-level real Q_{it} variables in each year. This measure of fundamentals is much more highly correlated with investment. In the top panel — which plots the level of I_t/K_{t-1} and the level of real Q_t — the year-to-year variation appears highly correlated but the series have slightly different trends. In the bottom panel we plot the differences of the two series against one another. These are clearly highly correlated — the raw correlation is about 0.5 and statistically significant from zero — and appear to move together in both the expansions and the one contraction during this sample period. As an aside, this correlation may be of significant use to forecasters, since the I/B/E/S dataset is updated frequently.

We conclude that this formulation of the neoclassical model appears to provide a reasonable description of the cyclical fluctuations of aggregate investment over our sample period. To our knowledge, this is the first time that a neoclassical variable with such robust *time-series* properties has been identified.

4.6 Sensitivity Analysis

In this subsection, we address two potentially important criticisms of our use of the I/B/E/S earnings data and summarize the results of other sensitivity exercises. The first criticism involves the use of net income as our liquidity variable. This variable differs from the cash flow measures used by previous authors because it does not add back depreciation charges to earnings. As a result, our measure omits a portion of the firm's recently generated cash. Also, we lag our liquidity variable by one period, in order to measure funds available to the firm at the start of period t; in contrast, other authors often use cash flow generated during the same period as the investment spending (see, e.g., Gilchrist and Himmelberg 1995).[26] Clearly, our ability to reproduce the strong cash effects found in past studies suggests that the I/B/E/S earnings data do not bias against finding liquidity effects. However, as a check, table 5 provides the results when we estimate the investment equation using the current-period Compustat measure of internal funds. In all other respects, this equation is identical to the first-differenced GMM specification in table 3.

As can be seen by reading across the row labeled Compustat CF_{it}, the coefficient estimates on cash flow for this alternative formulation look very similar to those in table 3. They are statistically insignificant in the full sample and in each of the *a priori* "constrained" subsamples. Thus, our results hold up when we use the liquidity variable employed in a number of previous studies.[27]

The second potential criticism concerns the timing of the I/B/E/S earnings expectations. When we constructed the dataset, we used the first forecast available in the firm's fiscal year, and called this our "beginning-of-period" forecast. Technically, analysts issue their initial forecast shortly after the fiscal year begins, so the forecasts

[26] This latter step puzzles us, since the first term in the PDV calculation for q in equation (4) should include the earnings generated during the first period in which the investment good is in service. Indeed, this term should receive the largest weight in the calculation of q.

[27] We obtained qualitatively similar results when we used operating income before depreciation (Compustat data item 13), which includes the cash flow from financing and investing activities, as our liquidity measure.

could be correlated with the current-period rational expectations error. Moreover, the one-period-ahead forecast for net income is highly correlated with our liquidity variable, which could reduce the power of our previous tests to identify liquidity effects if they are present. To address these concerns, table 6 reports our basic GMM estimation in first-differences on the full sample and for the splits, only this time we remove the one-period-ahead forecasts, ECF_{it}, from our construction of real Q_{it} and from our instrument set. As can be seen by reading across the row labeled $CF_{i,t-1}$, even these results provide no support for the view that liquidity constraints affect the firms in our sample.

We have done more empirical work, which we summarize here, to study the robustness of our results. We examined whether our results were affected by different rules for deleting outliers. When we deleted fewer outliers in the ratio of investment to beginning-of-period capital, tax-adjusted Q_{it}, and real Q_{it}, the coefficient estimates on fundamentals were smaller but still statistically significant. The intuition is provided by figure 4, which shows that investment responds less to fundamentals for higher values of real Q_{it}. When we deleted fewer outliers in the I/B/E/S or Compustat liquidity variables our results were unaffected. We experimented with different subsamples that might contain liquidity constrained firms. For example, we studied the firms identified by Gilchrist and Himmelberg (1995) as liquidity constrained for which we have data and the firms that are followed by only a single analyst. The results from these subsamples were qualitatively identical to those reported for the other subsamples. As an alternative way to address whether the dating of the first earnings forecasts biased the results, we examined whether our results were affected by excluding firms that have their first forecast more than 2 months from the beginning of the fiscal year. Again our qualitative results were identical. As yet another robustness check, we estimated the specifications in tables 2, 3, 5, and 6 in levels and the results were also qualitatively unaffected. Finally, we included industry dummy variables to supplement the year dummies and our results were also similar.

5 Conclusion

Our results suggest that the neoclassical model of investment behavior fits the firm-level data extremely well, confirming previous, more restrictive, studies by Cummins et al. (1994, 1995).[28] In contrast to those studies, however, we show that neoclassical fundamentals matter outside of selected periods with natural experiments. Furthermore, we find that our simple measure of fundamentals — real Q_t — provides a reasonable description of aggregate investment over the business cycle. Complementing these findings, we show that liquidity constraints affect investment behavior far less than previously believed, if at all, for firms covered by securities analysts. These firms account for a large majority of the total sales and investment by US companies.

Most researchers would agree that some firms do face liquidity constraints.[29] The real issue is the size of this group relative to the group of unconstrained firms. Our results suggest that the constrained group excludes firms covered by securities analysts, consistent with theories based on asymmetric information. Another possible dividing line may be temporal. That is, liquidity constraints may have been more widespread before the mid-1980s, when analyst coverage for the bulk of our sample begins. Since the coverage by analysts has grown significantly over time, it is possible that binding liquidity constraints were more important for understanding investment fluctuations before the mid-1980s. Thus, future research should work to identify signs of constrained behavior in firms not covered by analysts, although our results caution against attempting to do so by interpreting cash flow coefficients in investment equations estimated with poor measures of fundamentals.

[28]Studies by Meghir and Weber (1996) and Runkle (1991) have reached similar conclusions about the neoclassical model of consumption.

[29]For example, Holtz-Eakin, Joulfaian, and Rosen (1990) provide compelling evidence that individuals who inherit wealth are more likely to start small businesses; such a correlation suggests that capital markets are not completely efficient.

A Construction of Tax-Adjusted Average Q

Tax-adjusted average Q is defined as:

$$Q_{it} = \frac{1}{(1-\tau_t)}\left[\left(\frac{L_{it}V_{it} + B_{it} - A_{it}}{K^*_{i,t-1}}\right) - p_t(1-\Gamma_{it})\right],$$

where τ is the marginal corporate tax rate; L is an indicator variable equaling unity if the firm is not paying dividends and $(1-m_t)/(1-z_t)$ if the firm is paying dividends, where m is the personal tax rate on dividends and z is an accrual-equivalent capital gains tax rate; V is the value of the firm's equity; B is the market value of outstanding debt; A is the present value of the depreciation allowances on investment made before period t; K^* is the replacement value of the firm's capital stock including inventories; p is the price of capital goods relative to the price of output; and Γ is the tax benefit of investing. For example, with an investment tax credit at rate k, Γ is:

$$\Gamma_{it} = k_{it} + \sum_{s=t}^{\infty}(1 + r_s + \pi^e_s)^{-t}\tau_s DEP_{is}(s-t),$$

where r is the default-risk-free real interest rate (assumed to equal 3 percent), and $DEP_{is}(a)$ is the depreciation allowance permitted an asset of age a discounted at a nominal rate that includes the expected inflation rate π^e.

The market value of equity is the sum of the market value of a firm's common equity (defined as the number of common shares outstanding multiplied by end-of-year common stock price) and the market value of preferred stock (defined as the firm's preferred dividend payout divided by S&P's preferred dividend yield obtained from Citibase). The value of firm debt is the sum of short-term debt and long-term debt, both measured at book values. The replacement value of the capital stock is calculated from the standard perpetual inventory method with a firm-level rate of economic depreciation constructed using the method in Cummins et al. (1994). The replacement value of inventories is also constructed using the perpetual inventory method.

We use several other data items for the calculation of tax-adjusted Q. Data on expected inflation are taken from the Livingston Survey (provided by the Federal Reserve Board). The value of the firm's required rate of return is calculated as the difference between the firm's interest rate and expected inflation.[30] Tax parameters are updated from those used in Cummins et al. (1994); we construct asset-specific investment tax credits to reflect the firm's two-digit SIC code asset composition.

Firm data were deleted or modified according to the following rules. If the estimated firm depreciation rate was negative or greater than unity, we set it equal to the mean for firms in the same four-digit SIC code. If the replacement value of the capital stock or inventory was negative, we set it equal to book value. If dividend payouts on preferred stock were reported as missing, we set them equal to zero. If no inventory valuation method was specified, we assume the firm used the first-in-first-out (FIFO) system. If multiple valuation methods were reported, our calculations assume that the primary method is used.

[30]When available, we use Compustat's S&P bond rating to identify the firm's interest rate, and the associated rate is obtained from Citibase. Otherwise we use the BAA bond rate.

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Table 1: Means, Medians, and Standard Deviations of Sample Variables

Year	Number of Firms	I_t/K_{t-1}	Real Q_t	Tax Adjusted Q_t	I/B/E/S CF_t	Compustat CF_t
1984	376	0.316	1.422	2.588	0.265	0.457
		(0.270)	(1.038)	(2.070)	(0.181)	(0.365)
		[0.179]	[1.360]	[1.916]	[0.252]	[0.342]
1985	440	0.322	1.313	3.372	0.244	0.420
		(0.288)	(0.987)	(2.879)	(0.172)	(0.344)
		[0.177]	[1.150]	[2.293]	[0.232]	[0.301]
1986	503	0.295	1.257	3.541	0.221	0.392
		(0.263)	(0.945)	(2.979)	(0.159)	(0.335)
		[0.174]	[1.154]	[2.561]	[0.213]	[0.283]
1987	513	0.291	1.329	2.464	0.240	0.411
		(0.261)	(0.968)	(2.043)	(0.178)	(0.344)
		[0.171]	[1.302]	[1.879]	[0.227]	[0.296]
1988	588	0.297	1.442	2.516	0.277	0.445
		(0.265)	(1.067)	(2.091)	(0.205)	(0.375)
		[0.172]	[1.339]	[1.872]	[0.251]	[0.304]
1989	669	0.317	1.496	2.986	0.282	0.432
		(0.283)	(1.086)	(2.337)	(0.207)	(0.349)
		[0.180]	[1.397]	[2.259]	[0.263]	[0.304]
1990	738	0.299	1.369	2.347	0.258	0.397
		(0.263)	(0.979)	(1.720)	(0.180)	(0.320)
		[0.161]	[1.312]	[2.056]	[0.247]	[0.293]
1991	795	0.260	1.343	2.953	0.240	0.361
		(0.225)	(0.975)	(2.167)	(0.167)	(0.301)
		[0.154]	[1.283]	[2.538]	[0.232]	[0.269]
1992	850	0.269	1.316	3.074	0.236	0.350
		(0.240)	(0.957)	(2.405)	(0.167)	(0.290)
		[0.164]	[1.238]	[2.534]	[0.231]	[0.245]
1993	900	0.285	1.340	3.236	0.241	0.329
		(0.244)	(0.976)	(2.629)	(0.176)	(0.275)
		[0.169]	[1.251]	[2.474]	[0.229]	[0.248]
1994	812	0.282	1.407	2.828	0.258	0.351
		(0.239)	(1.028)	(2.210)	(0.183)	(0.288)
		[0.163]	[1.313]	[2.280]	[0.240]	[0.249]
1995	574	0.281	1.493	3.320	0.282	0.350
		(0.247)	(1.021)	(2.540)	(0.197)	(0.280)
		[0.167]	[1.478]	[2.664]	[0.270]	[0.273]
Total	7758	0.290	1.376	2.937	0.253	0.384
		(0.253)	(0.995)	(2.312)	(0.180)	(0.313)
		[0.169]	[1.301]	[2.346]	[0.241]	[0.282]

The medians of variables are in parentheses below the means. The standard deviations of variables are in square brackets below the means. I/B/E/S CF_t represents the ratio of net income to beginning-of-period capital stock. Compustat CF_t represent the ratio of cash flow to beginning-of-period capital stock.

Table 2: OLS Estimates of First Differenced Investment Equations using Tax-Adjusted Q and Real Q

	Full Sample						Manufacturing Sample					
Parameter	All Firms		No Bond Rating		No Dividend		All Firms		No Bond Rating		No Dividend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intercept	-0.028	-0.025	-0.031	-0.027	-0.041	-0.032	-0.027	-0.025	-0.025	-0.023	-0.020	-0.005
	(0.009)	(0.009)	(0.014)	(0.013)	(0.032)	(0.030)	(0.014)	(0.013)	(0.019)	(0.018)	(0.037)	(0.033)
Tax Adjusted Q_{it}	0.008	—	0.010	—	0.018	—	0.007	—	0.010	—	0.020	—
	(0.002)		(0.003)		(0.004)		(0.002)		(0.003)		(0.005)	
Real Q_{it}	—	0.089	—	0.085	—	0.107	—	0.079	—	0.071	—	0.088
		(0.010)		(0.012)		(0.018)		(0.010)		(0.013)		(0.021)
$CF_{i,t-1}$	0.351	0.022	0.337	0.013	0.297	-0.159	0.339	0.054	0.320	0.062	0.287	-0.074
	(0.025)	(0.041)	(0.031)	(0.055)	(0.041)	(0.085)	(0.030)	(0.045)	(0.037)	(0.056)	(0.049)	(0.104)
Number of Firms	1177	1177	776	776	333	333	631	631	423	423	163	163
Number of Obs	5404	5404	2591	2591	837	837	2898	2898	1443	1443	426	426

The dependent variable is the first difference of the ratio of investment to beginning-of-period capital, and the independent variables are the first differences of beginning-of-period tax-adjusted Q, real Q_{it} constructed using beginning-of-period I/B/E/S analysts' forecasts, and the ratio of lagged net income to beginning-of-period capital, $CF_{i,t-1}$. Robust standard errors on coefficients are in parentheses. Year dummies are included (but not reported) in all regressions. The estimation period is 1986-95. The "no dividend" sample is restricted to firms that do not pay dividends. The "no bond rating" sample is restricted to firms that do not have a bond rating from Standard & Poor's.

Table 3: GMM Estimates of First Differenced Investment Equations using Tax-Adjusted Q and Real Q

Parameter	Full Sample						Manufacturing Sample					
	All Firms		No Bond Rating		No Dividend		All Firms		No Bond Rating		No Dividend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intercept	0.062	-0.002	0.030	-0.006	0.086	-0.001	-0.088	0.006	0.040	0.005	0.228	0.021
	(0.125)	(0.009)	(0.023)	(0.008)	(0.066)	(0.009)	(0.081)	(0.011)	(0.030)	(0.009)	(0.117)	(0.003)
Tax Adjusted Q_{it}	0.188	—	0.135	—	0.213	—	0.105	—	0.108	—	0.239	—
	(0.059)		(0.054)		(0.070)		(0.054)		(0.054)		(0.090)	
Real Q_{it}	—	0.115	—	0.098	—	0.111	—	0.115	—	0.132	—	0.102
		(0.015)		(0.021)		(0.016)		(0.016)		(0.019)		(0.010)
$CF_{i,t-1}$	0.030	-0.005	-0.089	-0.081	0.003	-0.008	-0.147	-0.002	0.008	-0.152	-0.158	-0.094
	(0.320)	(0.020)	(0.219)	(0.070)	(0.255)	(0.029)	(0.160)	(0.016)	(0.222)	(0.056)	(0.239)	(0.025)
Sargan statistic	11.4	126.1	14.5	126.1	7.29	69.8	9.88	94.7	11.4	70.4	2.98	63.2
p-value	(0.123)	(0.000)	(0.043)	(0.000)	(0.399)	(0.483)	(0.196)	(0.026)	(0.124)	(0.465)	(0.887)	(0.705)
Number of Firms	809	809	472	472	208	208	447	447	274	274	121	121
Number of Obs	3816	3816	1654	1654	564	564	2108	2108	974	974	345	345

The dependent variable is the first difference of the ratio of investment to beginning-of-period capital, and the independent variables are the first differences of beginning-of-period tax-adjusted Q, real Q_{it} constructed using beginning-of-period I/B/E/S analysts' forecasts, and the ratio of lagged net income to beginning-of-period capital, $CF_{i,t-1}$. Robust standard errors on coefficients are in parentheses. Instrumental variables are the period $t-2$ and $t-3$ values of the ratios of investment to beginning-of-period capital; the ratios of the analysts' forecasts of one-year-ahead and two-year-ahead earnings to beginning-of-period capital; and the long-term growth forecasts. Year dummies are included (but not reported) in all regressions. The estimation period is 1988-95. The "no dividend" sample is restricted to firms that do not pay dividends. The "no bond rating" sample is restricted to firms that are do not have a bond rating from Standard & Poor's.

Table 4: Semiparametric Estimates of the Partially-Linear Investment Equations: Coefficient Estimates on Lagged Liquidity

Parameter	Full Sample						Manufacturing Sample					
	All Firms		No Bond Rating		No Dividend		All Firms		No Bond Rating		No Dividend	
	Levels (1)	Differences (2)	Levels (3)	Differences (4)	Levels (5)	Differences (6)	Levels (7)	Differences (8)	Levels (9)	Differences (10)	Levels (11)	Differences (12)
Third Order Polynomial Series	0.000	-0.000	-0.036	-0.106	0.025	-0.024	0.000	-0.000	-0.055	-0.131	-0.002	-0.040
	(0.001)	(0.001)	(0.026)	(0.025)	(0.034)	(0.035)	(0.001)	(0.001)	(0.031)	(0.030)	(0.041)	(0.043)
Fourth Order Polynomial Series	0.000	0.000	-0.031	-0.094	0.026	-0.018	0.000	-0.000	-0.058	-0.119	0.004	-0.030
	(0.001)	(0.000)	(0.025)	(0.025)	(0.035)	(0.035)	(0.001)	(0.001)	(0.032)	(0.031)	(0.043)	(0.044)
Projection Pursuit	0.000	-0.000	-0.032	-0.110	0.019	-0.008	0.001	-0.000	-0.054	-0.123	0.007	-0.016
	(0.001)	(0.001)	(0.026)	(0.024)	(0.035)	(0.034)	(0.001)	(0.001)	(0.032)	(0.030)	(0.041)	(0.040)
MARS	0.000	0.000	-0.034	-0.112	0.022	-0.011	0.001	-0.000	-0.055	-0.120	0.009	-0.021
	(0.001)	(0.001)	(0.026)	(0.025)	(0.034)	(0.035)	(0.001)	(0.001)	(0.032)	(0.031)	(0.042)	(0.040)
Number of Obs	7982	7982	3946	3946	1648	1648	4354	4354	2226	2226	1452	1452

The dependent variable is the level or first difference of the ratio of investment to beginning-of-period capital. The coefficient estimates are on $CF_{i,t-1}$ using the nonparametric methods shown in the first column to approximate marginal q. The asymptotic standard errors on the coefficients are in parentheses. The variables used to approximate marginal q are the beginning-of-period I/B/E/S data for ECF_{it}, $ECF_{i,t+1}$, and $EGROW_i$. The differences model also includes year dummies (not reported); see section 2.3 for further discussion of model specification. The estimation period is 1985–1995.

Table 5: GMM Estimates of First Differenced Investment Equations using Tax-Adjusted Q, Real Q, and Compustat Cash Flow

	Full Sample						Manufacturing Sample					
Parameter	All Firms		No Bond Rating		No Dividend		All Firms		No Bond Rating		No Dividend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intercept	0.042	0.003	0.027	-0.009	0.073	-0.002	0.059	0.005	0.041	-0.001	0.185	0.013
	(0.014)	(0.005)	(0.016)	(0.007)	(0.067)	(0.009)	(0.019)	(0.007)	(0.022)	(0.0 08)	(0.102)	(0.004)
Tax Adjusted Q_{it}	0.202	—	0.134	—	0.192	—	0.162	—	0.111	—	0.204	—
	(0.061)		(0.047)		(0.087)		(0.055)		(0.047)		(0.086)	
Real Q_{it}	—	0.118	—	0.085	—	0.108	—	0.114	—	0.120	—	0.092
		(0.022)		(0.019)		(0.016)		(0.020)		(0.019)		(0.007)
Compustat CF_{it}	-0.102	0.052	-0.064	-0.018	0.131	-0.003	-0.000	-0.005	0.016	-0.063	0.006	-0.055
	(0.228)	(0.065)	(0.145)	(0.049)	(0.191)	(0.035)	(0.148)	(0.052)	(0.130)	(0.042)	(0.178)	(0.016)
Sargan statistic	18.1	119.7	14.4	82.7	7.50	70.4	9.28	95.1	10.9	72.6	3.77	62.6
p-value	(0.012)	(0.000)	(0.045)	(0.140)	(0.379)	(0.463)	(0.233)	(0.025)	(0. 141)	(0.394)	(0.806)	(0.722)
Number of Firms	809	809	472	472	208	208	447	447	274	274	121	121
Number of Obs	3816	3816	1654	1654	564	564	2108	2108	974	974	345	345

The dependent variable is the first difference of the ratio of investment to beginning-of-period capital, and the independent variables are the first differences of beginning-of-period tax-adjusted Q, real Q_{it} constructed using beginning-of-period I/B/E/S analysts' forecasts, and the ratio of current-period Compustat cash flow to beginning-of-period capital, CF_{it}. Robust standard errors on coefficients are in parentheses. Instrumental variables are the period $t-2$ and $t-3$ values of the ratios of investment to beginning-of-period capital; the ratios of the analysts' forecasts of one-year-ahead and two-year-ahead earnings to beginning-of-period capital; and the long-term growth forecasts. Year dummies are included (but not reported) in all regressions. The estimation period is 1988–95. The "no dividend" sample is restricted to firms that do not pay dividends. The "no bond rating" sample is restricted to firms that do not have a bond rating from Standard and Poor's.

Table 6: GMM Estimates of First Differenced Investment Equations using Real Q

	Full Sample						Manufacturing Sample					
Parameter	All Firms		No Bond Rating		No Dividend		All Firms		No Bond Rating		No Dividend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intercept	0.004	0.005	-0.006	-0.007	-0.013	-0.011	0.009	0.009	0.003	0.001	0.007	0.010
	(0.009)	(0.010)	(0.008)	(0.008)	(0.016)	(0.017)	(0.011)	(0.012)	(0.010)	(0.0 10)	(0.019)	(0.020)
Real Q_{it}	0.152	—	0.123	—	0.102	—	0.128	—	0.134	—	0.096	—
	(0.019)		(0.024)		(0.021)		(0.020)		(0.026)		(0.018)	
Real $Q2_{it}$	—	0.192	—	0.145	—	0.125	—	0.161	—	0.152	—	0.115
		(0.024)		(0.029)		(0.025)		(0.020)		(0.032)		(0.007)
$CF_{i,t-1}$	0.014	0.014	-0.182	-0.152	0.027	0.036	0.005	0.005	-0.114	-0.065	-0.097	-0.093
	(0.039)	(0.039)	(0.061)	(0.059)	(0.057)	(0.057)	(0.018)	(0.018)	(0.073)	(0 .072)	(0.042)	(0.041)
Sargan statistic	101.9	102.0	66.5	66.5	62.7	62.9	79.2	80.0	61.0	62.1	52.9	53.2
p-value	(0.000)	(0.000)	(0.118)	(0.119)	(0.196)	(0.191)	(0.014)	(0.012)	(0. 141)	(0.209)	(0.518)	(0.504)
Number of Firms	809	809	472	472	208	208	447	447	274	274	121	121
Number of Obs	3816	3816	1654	1654	564	564	2108	2108	974	974	345	345

The dependent variable is the first difference of the ratio of investment to beginning-of-period capital, and the independent variables are the first differences of real Q_{it} constructed using beginning-of-period I/B/E/S analysts' forecasts, real $Q2_{it}$ constructed like real Q_{it} but omitting the one-year-ahead forecast, and the ratio of lagged net income to beginning-of-period capital, $CF_{i,t-1}$. Robust standard errors on coefficients are in parentheses. Instrumental variables are the period $t-2$ and $t-3$ values of the ratios of investment to beginning-of-period capital; the ratios of the analysts' forecasts of one-year-ahead and two-year-ahead earnings to beginning-of-period capital; and the long-term growth forecasts. Year dummies are included (but not reported) in all regressions. The estimation period is 1988-95. The "no dividend" sample is restricted to firms that do not pay dividends. The "no bond rating" sample is restricted to firms that do not have a bond rating from Standard and Poor's.

Figure 1: Kernel Regression Smoother of Investment as a Function of Cash Flow

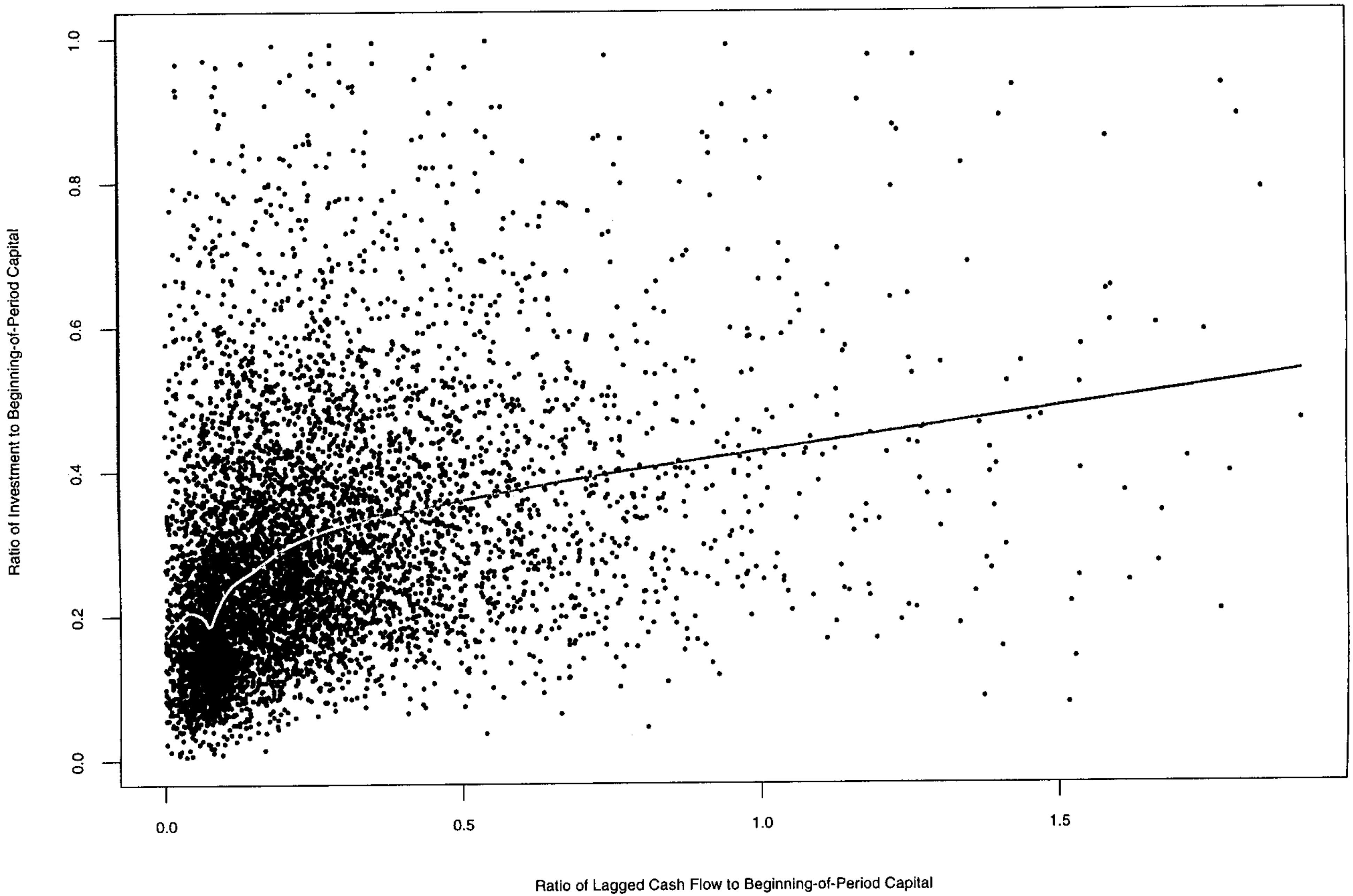


Figure 2: Kernel Regression Smoother of Real Q as a Function of Cash Flow

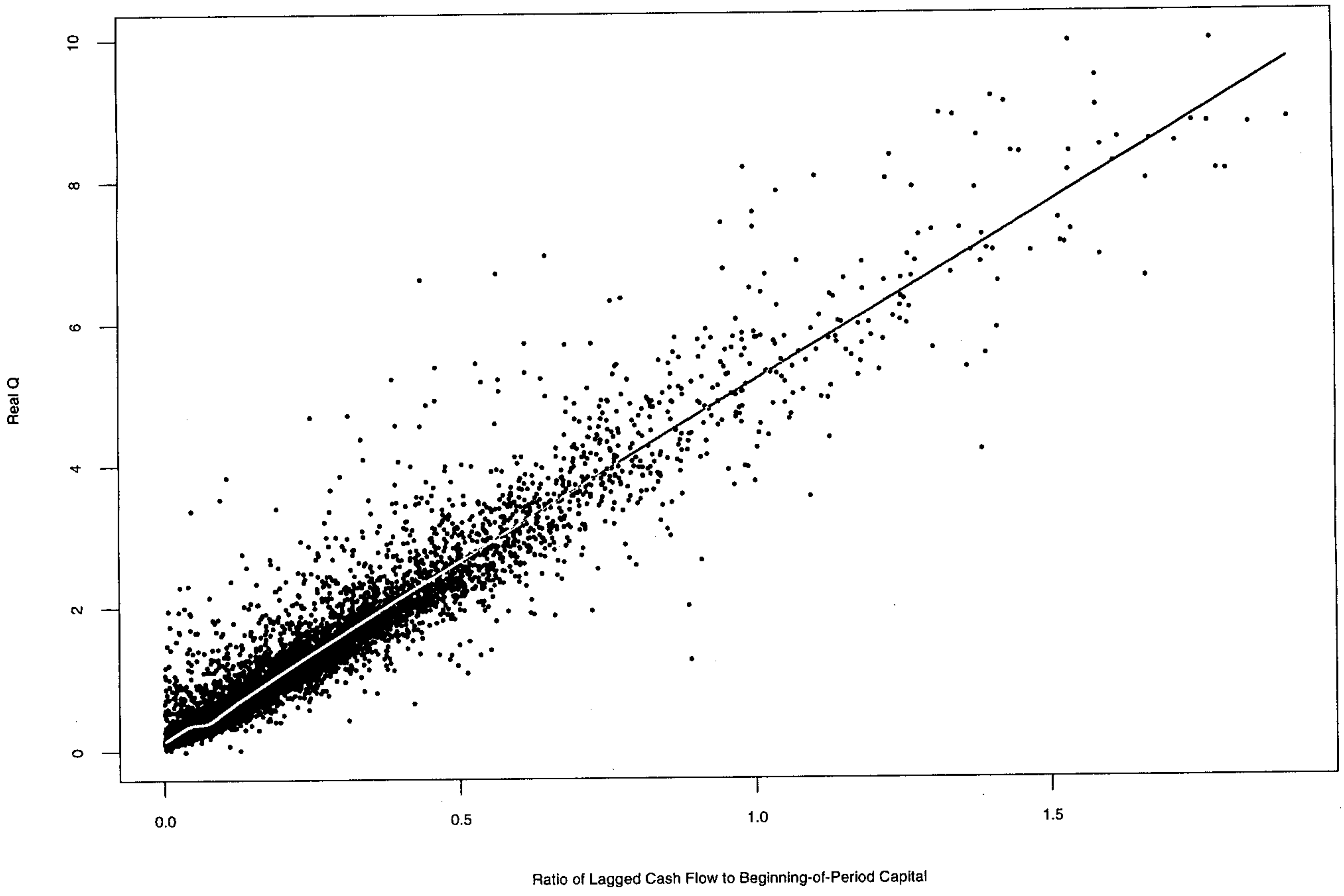


Figure 3: Kernel Regression Smoother of Investment as a Function of Cash Flow Controlling for Real Q

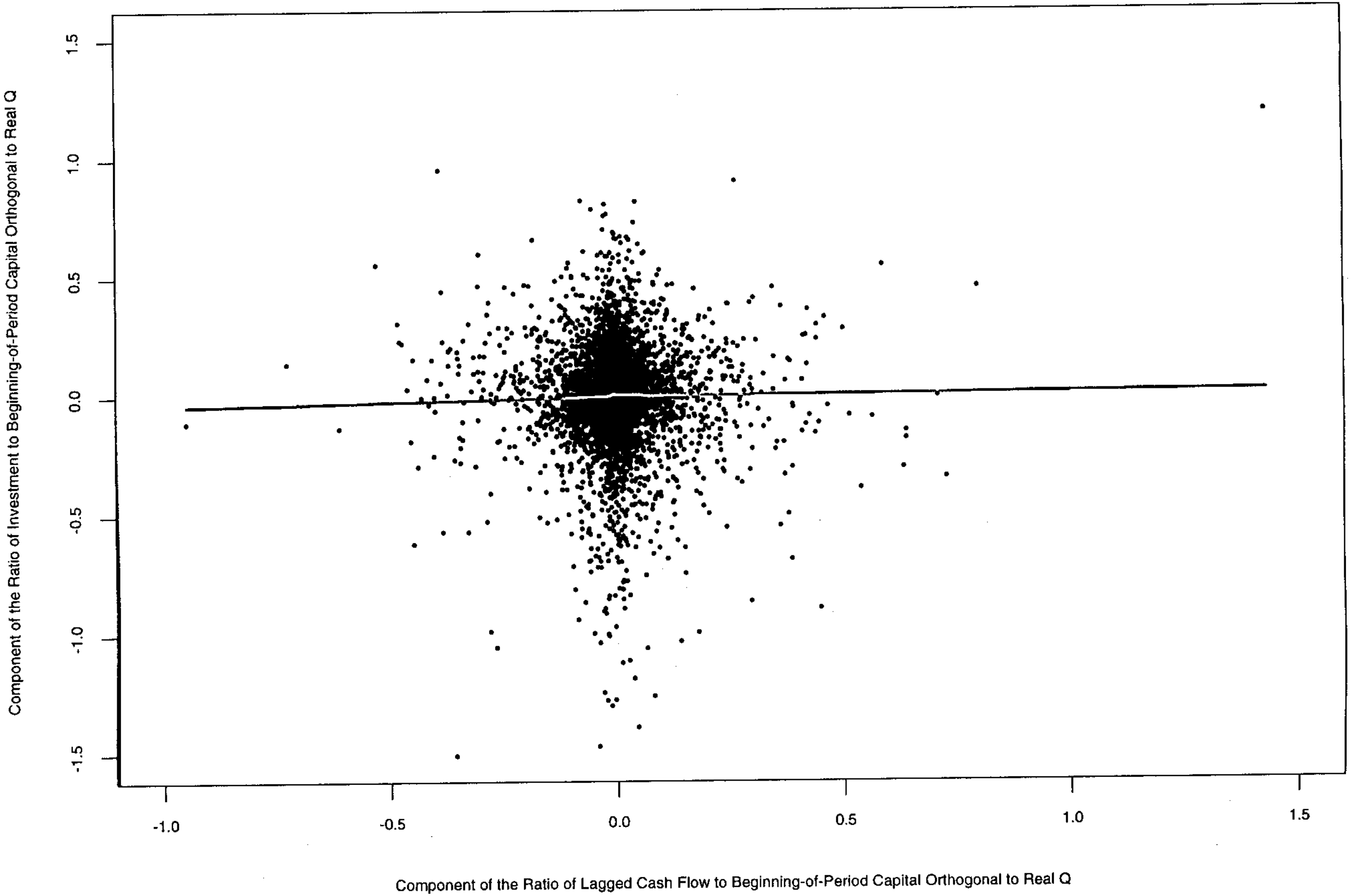


Figure 4: Kernel Regression Smoother of Investment as a Function of Real Q

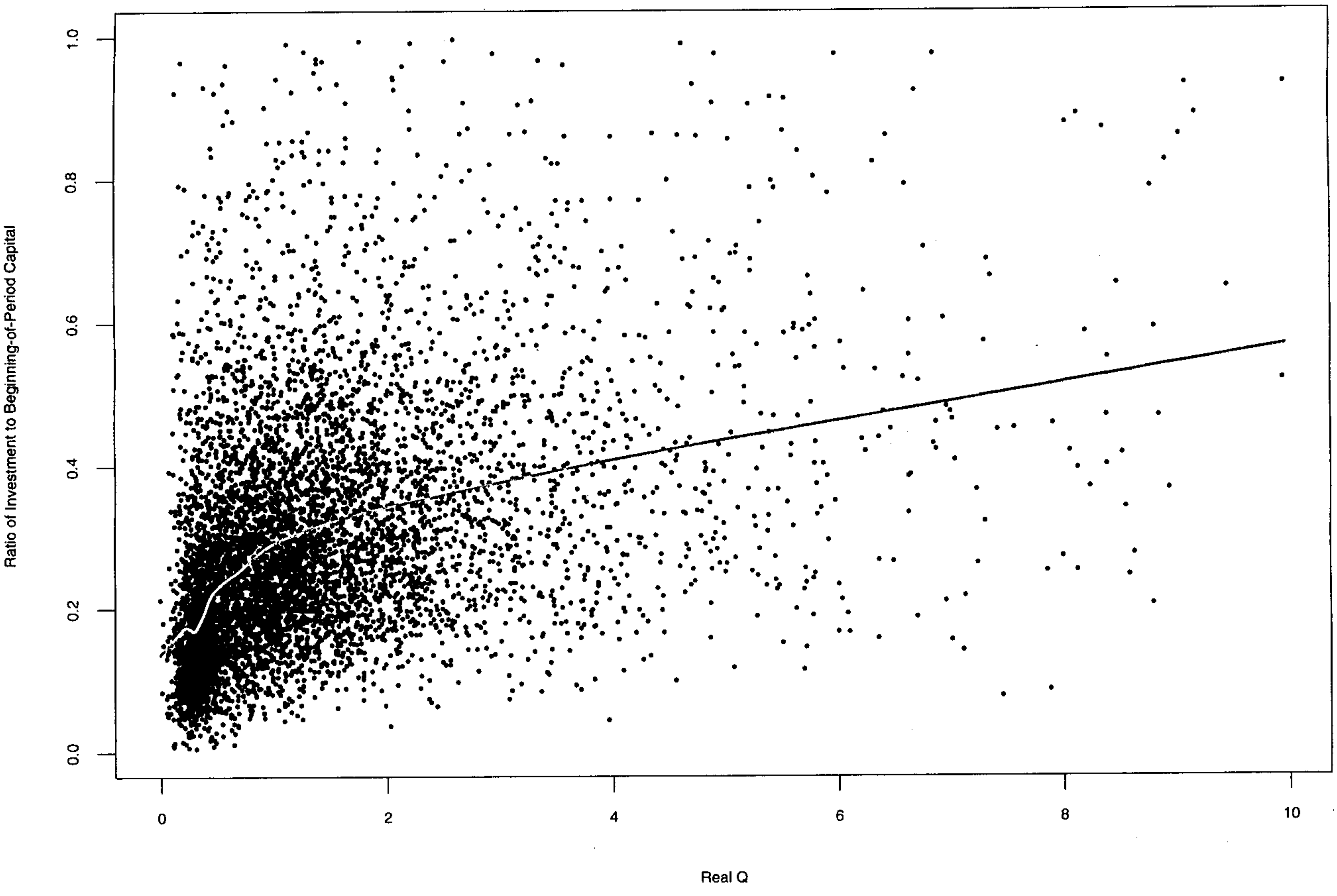
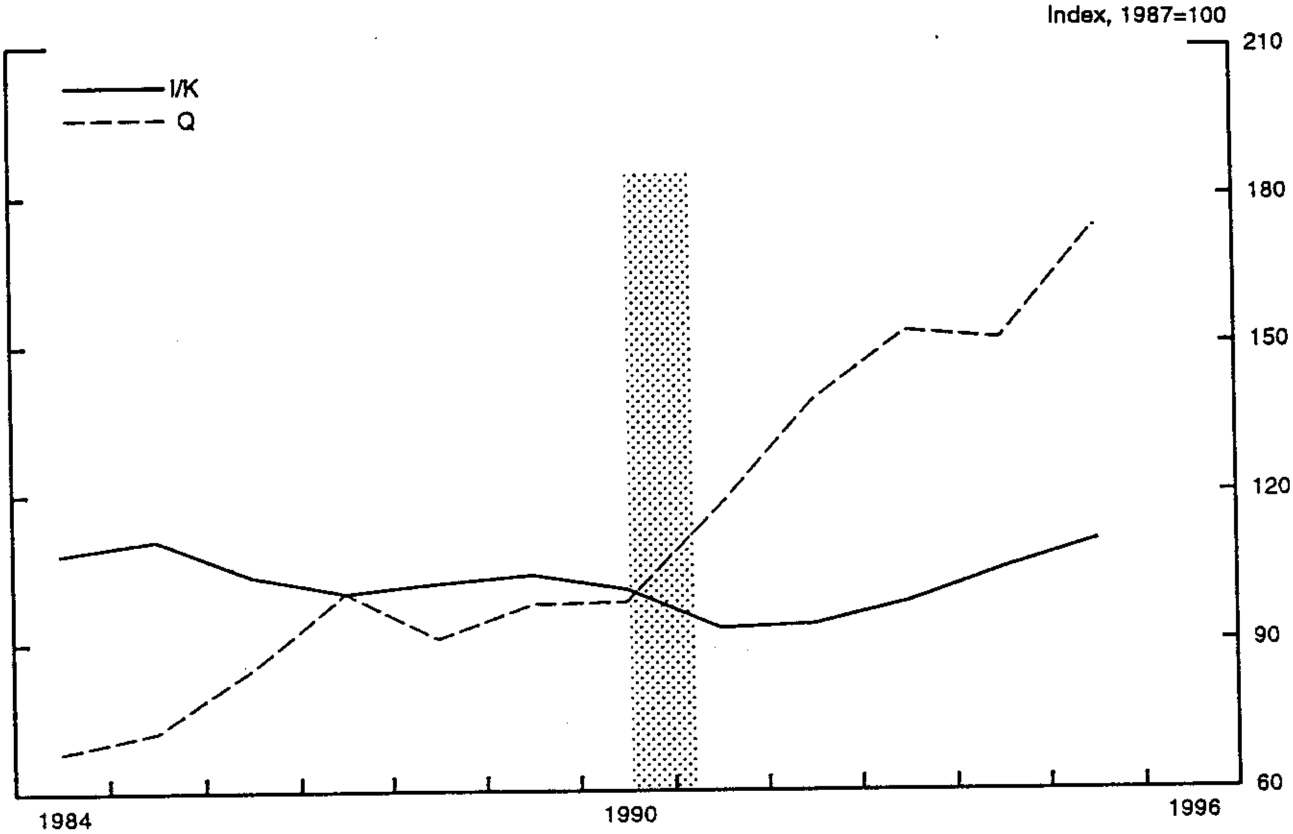
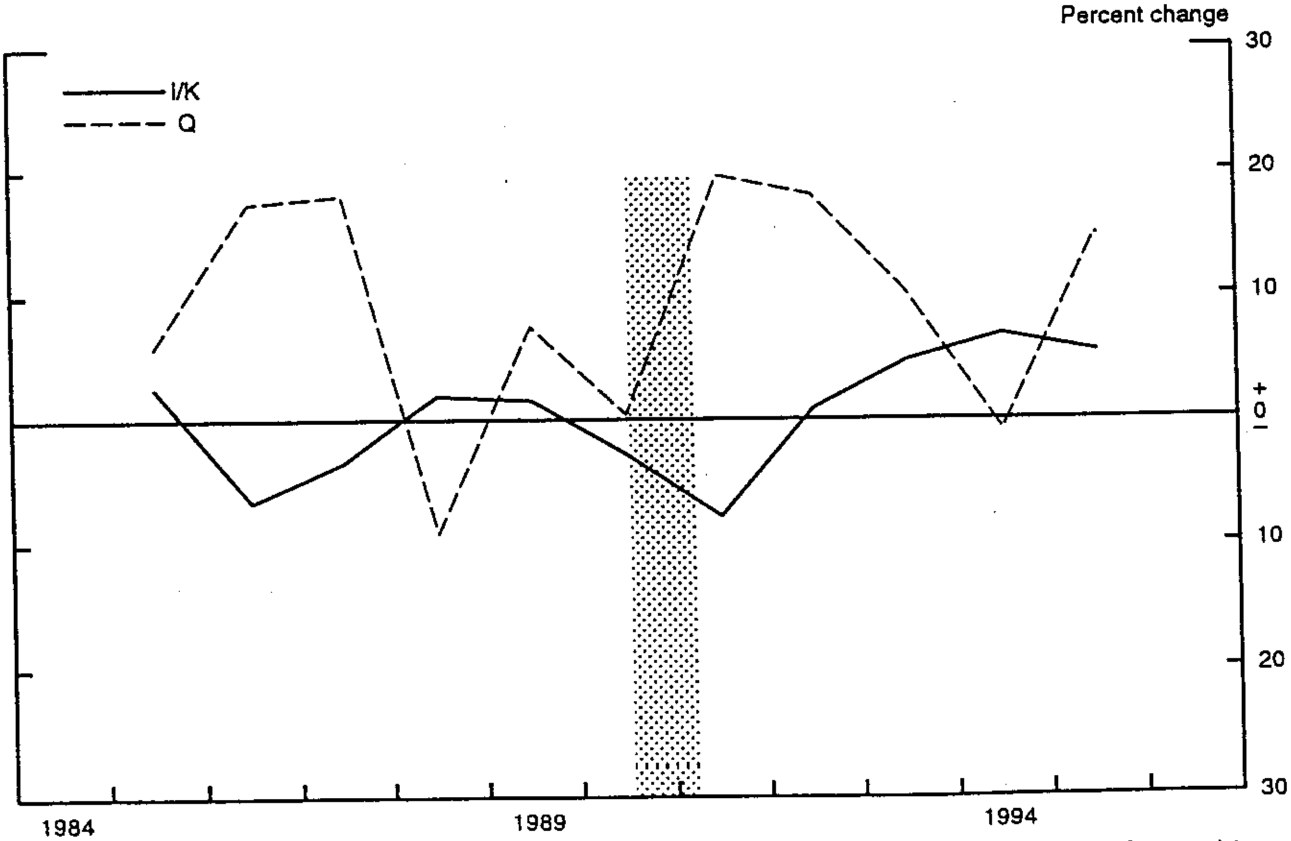


Figure 5
Tobin's Q

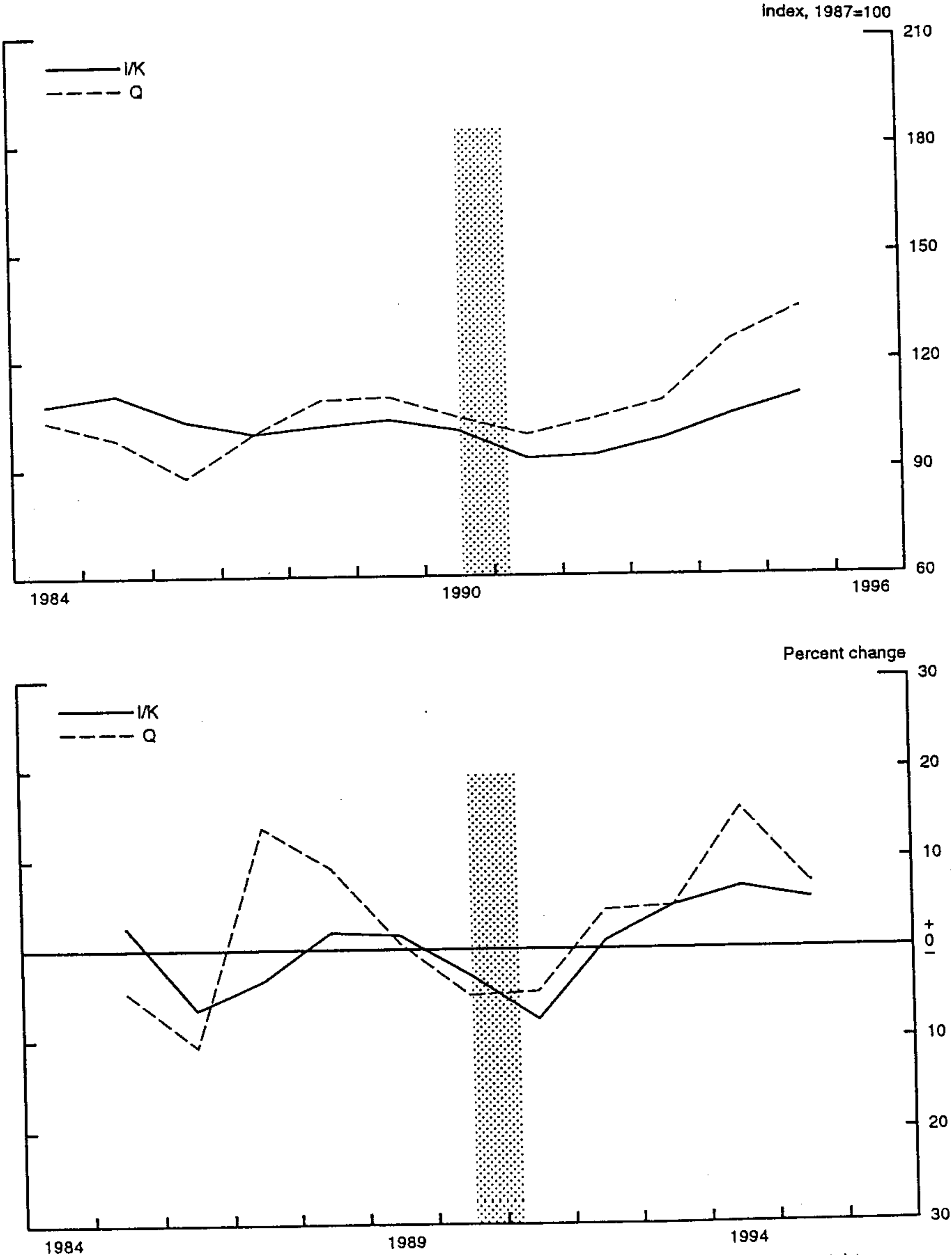




I/K is BEA's business fixed investment over capital stock; Q is constructed by authors from flow of funds Federal Reserve data.

Figure 6

Expected Fundamental Q



I/K is BEA's business fixed investment over capital stock; Q is constructed by authors from IBES and Compustat data.