A Supply Approach to Valuation

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A new methodology for equity valuation arises from the perspective of managers' supply of capital assets. Under q-theory, managers optimally adjust the supply of assets to changes in their market value. The first-order condition of investment then provides a valuation equation that infers asset prices from managers' costs of supplying the assets. This equation fits well the Tobin's q levels across many testing assets, including portfolios formed on q. With current investment-to-capital as the only input, the supply approach does not require cash flow forecasts or discount rate estimates, both of which are notoriously difficult to obtain in practice. (*JEL* D21, E22, G12)

What determines equity valuation? This economic question is immensely important in theory and practice. A vast literature has built on present value models such as the dividend discounting and the residual income models for equity valuation (e.g., Ohlson 1995; Dechow, Hutton, and Sloan 1999; Frankel and Lee 1998). Widely practiced in the financial services industry, valuation is at the core of standard business school curricula around the world with many textbook treatments (e.g., Lundholm and Sloan 2007; Palepu and Healy 2008; Koller, Goedhart, and Wessles 2010; Penman 2010). Working

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from the perspective of investors' *demand* of risky securities, the traditional valuation approach calculates the present value of future dividends. Although conceptually sound, its implementation often involves ad hoc assumptions that leave at least some room for an alternative approach.

In asset pricing, research on the cross-section of valuation seems scarce. Reflecting on the surprising lack of valuation research in asset pricing, Cochrane (2011, 1063, original emphasis) writes: "We have to answer the central question, what is the source of *price* variation? When did our field stop being 'asset pricing' and become 'asset expected returning'? Why are betas exogenous? A lot of price variation comes from discount-factor news. What sense does it make to 'explain' expected returns by the covariation of expected return shocks with market return shocks? Market-to-book ratios should be our *left-hand* variable, the thing we are trying to *explain*, not a sorting characteristic for expected returns. Focusing on expected returns and betas rather than prices and discounted cashflows makes sense in a two-period or i.i.d. world, since in that case betas are all cashflow betas. It makes much less sense in a world with time-varying discount rates."

We take a first stab at the all-important valuation question from the perspective of managers' *supply* of capital assets. The idea is simple. Managers, if behaving optimally, will adjust the supply of capital assets to their changes in the market value. In particular, managers will invest in capital assets until the marginal benefits of one extra unit of assets (called marginal q, which is the present value of all the future cash flows generated by this extra unit) equate the marginal costs of supplying this extra unit. With a specified capital adjustment technology, we can infer the marginal costs of investment (and therefore marginal q). With constant returns to scale, we can then use the inferred marginal q to value a firm's entire installed capital assets. In all, we can back out the value of capital assets from managers' costs of supplying such assets. By observing managers investing more, for instance, investors can infer a higher marginal q and a higher value for the assets.

Formally, we develop the q-theory of investment as a valuation tool to pin down the levels of asset prices in the cross-section. The key valuation equation emerges under constant returns to scale (the Hayashi [1982] conditions). Tobin's q (the market value over the book value of capital assets) equals marginal q, which can be inferred from investment data via a specified adjustment costs function. We incorporate corporate taxes, leverage, time-varying capital depreciation, and nonlinear marginal costs of investment into a parameterized investment model. We use generalized methods of moments (GMM) to evaluate the model's fit in matching average Tobin's q across a variety of testing assets. We focus primarily on deciles formed on Tobin's q because sorting on q by construction produces the largest possible spread in q (which we call the valuation spread) in the cross-section.

In general equilibrium, the demand approach and the supply approach to valuation are complementary. One can read the market price from either the demand or the supply curve of an asset. However, we see two practical advantages of the supply approach over the traditional demand approach. First, the only input that the supply approach requires is the *observable* current period investment-to-capital. As noted, through an estimated adjustment costs function, investment-to-capital leads to marginal q, which allows us to value a firm's installed capital assets. As such, the supply approach relieves us of the burden of forecasting earnings or cash flows many years into the future, a task that is challenging but necessary to implement the demand approach.

Second, by equating Tobin's q directly to the marginal costs of investment, the supply approach does not need to take a stand on the discount rate, which is another critical input for the demand approach. It is well known that the discount rate estimates from standard asset-pricing models are extremely imprecise, even at the industry level (e.g., Fama and French 1997).[1] In contrast, at least in principle, the parameters from the supply approach are technological in nature, and should be invariant to changes in optimizing behavior and economic policy (e.g., Lucas 1976). As such, the parameters via structural estimation should be more stable than the reduced-form parameters such as the discount rate in the standard valuation models.

Our central contribution is to develop q-theory as a valuation tool. When we use the investment model to match the valuation moments across the Tobin's q deciles, the model predicts a valuation spread of 4.45, which is close to the spread of 4.50 observed in the NYSE, Amex, and NASDAQ sample from 1963 to 2011. The error of 0.05 is about 1.1% of the valuation spread in the data. Across the q deciles, the average magnitude of the model errors is 0.07, which is about 4.5% of the average q across the deciles, 1.58. A scatter plot of average predicted q in the model against average realized q in the data across the deciles is almost perfectly aligned with the 45-degree line. Also, the model fits the valuation levels with reasonable adjustment costs (about 4.78% of sales). Adding the investment Euler equation (that anchors managers' investment decisions on economic fundamentals) into the GMM does not materially affect the model's fit on q.

Our econometric tests have enough power to detect model misspecifications. We stress-test the model by forcing it to fit the valuation levels across the 20, 50, and 100 portfolios formed on q. These more disaggregated portfolios admit larger valuation spreads than deciles: 6.59, 10.29, and 14.63, respectively.

[1] Reflecting on the current state of affairs, Penman (2010, 666) writes in a widely adopted valuation textbook: "Compound the error in beta and the error in the risk premium and you have a considerable problem. The CAPM, even if true, is quite imprecise when applied. Let's be honest with ourselves: No one knows what the market risk premium is. And adopting multifactor pricing models adds more risk premiums and betas to estimate. These models contain a strong element of smoke and mirrors." Unfortunately, valuation estimates from the present value models are extremely sensitive to the assumed discount rate. For instance, Lundholm and Sloan (2007, 193) lament: "The discount rate that you use in your valuation has a large impact on the result, yet you will rarely feel very confident that the rate you have assumed is the right one. The best we can hope for is a good understanding of what the cost of capital represents and some ballpark range for what a reasonable estimate might be."

A restricted model with linear marginal costs of investment (quadratic adjustment costs) is formally rejected at the 5% significance level even with the 10 and 20 portfolios. Intuitively, the relation between Tobin's q and investment-to-capital is linear with quadratic costs but convex with nonquadratic costs. For a given magnitude of the investment-to-capital spread, the convexity magnifies it to produce a larger valuation spread. As such, the convexity is quantitatively important for the benchmark model to fit the valuation data.

The investment model also does a good job in matching the valuation levels at the more disaggregated industry level. We use the 30-industry classifications per Fama and French (1997). With quintiles on Tobin's q as the testing assets within each industry, the average magnitude of the valuation errors is 0.12, which is about 8.7% of the average q across the industries, 1.38. Across the industries, the model predicts an average valuation spread of 2.16, which is about 94% of that in the data, 2.31. The industry-specific estimation also provides robust evidence indicating industry heterogeneity in the capital adjustment technology.

Our work expands investment-based asset pricing to the all-important economic question of equity valuation.[2] To the best of our knowledge, our work is among the first in this literature to tackle the cross-section of valuation. Our key finding that Tobin's q and investment are aligned on average at the portfolio level indicates measurement errors in q with a mean of zero. As such, our work lends support to Erickson and Whited (2000) and Gomes (2001), who argue that q-theory performs well in investment regressions once measurement errors in q are purged. However, by averaging out these errors, our econometric design differs in critical ways from the investment regressions. As such, the good fit of our model should not be interpreted as resurrecting the investment regressions.

The rest of the paper is organized as follows. Section 1 presents the model, Section 2 describes econometric methodology and data, Section 3 reports empirical results, and Section 4 concludes. Detailed derivations and supplementary results are furnished in an Internet Appendix.

1. The Model of the Firms

Firms choose costlessly adjustable inputs each period, taking their prices as given, to maximize operating profits (revenues minus expenditures on these inputs). Taking the operating profits as given, firms choose investment and debt to maximize the market equity. Operating profits for firm i at time t are given by $\Pi(K_{it}, X_{it})$, in which K_{it} is capital and X_{it} is a vector of exogenous aggregate

[2] Cochrane (1991, 1996) is the first to use the investment model to study asset prices. Zhang (2005) and I. Cooper (2006) construct dynamic investment models to explain the value premium. Liu, Whited, and Zhang (2009) use the investment model to explain the cross-section of expected returns. Belo (2010) uses the marginal rate of transformation as a stochastic discount factor in asset-pricing tests. Jermann (2010, 2013) studies the equity premium and the term structure of interest rates derived from firms' optimality conditions. I. Cooper and Priestley (2011) show that the negative relation between investment and average stock returns is likely due to risk.

and firm-specific shocks. The firm has a Cobb-Douglas production function with constant returns to scale. As such, $\Pi(K_{it}, X_{it}) = K_{it} \partial \Pi(K_{it}, X_{it})/\partial K_{it}$, and the marginal product of capital, $\partial \Pi(K_{it}, X_{it})/\partial K_{it} = \kappa Y_{it}/K_{it}$, in which κ is the capital's share in output and Y_{it} is sales.

Capital depreciates at an exogenous rate of δ_{it}, which is firm-specific and time-varying:

$$K_{it+1} = I_{it} + (1 - \delta_{it}) K_{it}, \tag{1}$$

in which I_{it} is investment. Firms incur adjustment costs when investing. The adjustment costs function, denoted $\Phi(I_{it}, K_{it})$, is increasing and convex in I_{it}, is decreasing in K_{it}, and has constant returns to scale in I_{it} and K_{it}. We allow the marginal costs of investment to be nonlinear:

$$\Phi(I_{it}, K_{it}) = \frac{1}{\nu} \left(\eta \frac{I_{it}}{K_{it}} \right)^{\nu} K_{it}, \tag{2}$$

in which $\eta > 0$ is the slope parameter and $\nu > 1$ is the curvature parameter. The case with $\nu = 2$ reduces to the standard quadratic functional form.

We allow firms to finance investment with one-period debt. At the beginning of period t, firm i issues an amount of debt, denoted B_{it+1}, that must be repaid at the beginning of $t+1$. Let r_{it}^B denote the gross corporate bond return on B_{it}. We can write taxable corporate profits as operating profits minus depreciation, adjustment costs, and interest expense: $\Pi(K_{it}, X_{it}) - \delta_{it} K_{it} - \Phi(I_{it}, K_{it}) - (r_{it}^B - 1) B_{it}$. Let τ_t denote the corporate tax rate. We define the payout of firm i as:

$$D_{it} \equiv (1 - \tau_t)[\Pi(K_{it}, X_{it}) - \Phi(K_{it}, K_{it})] - I_{it} + B_{it+1} - r_{it}^B B_{it} + \tau \delta_{it} K_{it} + \tau_t (r_{it}^B - 1) B_{it}, \tag{3}$$

in which $\tau_t \delta_{it} K_{it}$ is the depreciation tax shield and $\tau_t (r_{it}^B - 1) B_{it}$ is the interest tax shield.

Let M_{t+1} denote the stochastic discount factor from period t to $t+1$, which is correlated with the aggregate component of the productivity shock X_{it}. The firm chooses optimal capital investment and debt to maximize the cum-dividend market value of equity:

$$V_{it} \equiv \max_{\{I_{it+\triangle t}, K_{it+\triangle t+1}, B_{it+\triangle t+1}\}_{\triangle t=0}^{\infty}} E_t \left[\sum_{\triangle t=0}^{\infty} M_{t+\triangle t} D_{it+\triangle t} \right], \tag{4}$$

subject to a transversality condition given by $\lim_{T \to \infty} E_t [M_{t+T} B_{it+T+1}] = 0$. To express firm i's market value of equity and stock return as a function of observable firm characteristics, we let $P_{it} \equiv V_{it} - D_{it}$ be the ex-dividend equity value. The first-order condition of maximizing Equation (4) with respect to I_{it} implies that the market value of the firm is given by:

$$P_{it} + B_{it+1} = \left[1 + (1 - \tau_t) \eta^{\nu} \left(\frac{I_{it}}{K_{it}} \right)^{\nu - 1} \right] K_{it+1}. \tag{5}$$

In addition, combining the first-order conditions of maximizing Equation (4) with respect to I_{it} and K_{it+1} yields the investment Euler equation:

$$1+(1-\tau_t)\eta^\nu\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}=E_t\left[M_{t+1}\left[\begin{array}{c}(1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}}+\frac{\nu-1}{\nu}\left(\eta\frac{I_{it+1}}{K_{it+1}}\right)^\nu\right]+\delta_{it+1}\tau_{t+1}\\ +(1-\delta_{it+1})\left[1+(1-\tau_{t+1})\eta^\nu\left(\frac{I_{it+1}}{K_{it+1}}\right)^{\nu-1}\right]\end{array}\right]\right]. \tag{6}$$

Dividing both sides by the left-hand side implies that $E_t[M_{t+1}r^I_{it+1}]=1$, in which r^I_{it+1} is the investment return, defined as:

$$r^I_{it+1}\equiv\frac{(1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}}+\frac{\nu-1}{\nu}\left(\eta\frac{I_{it+1}}{K_{it+1}}\right)^\nu\right]+\delta_{it+1}\tau_{t+1}+(1-\delta_{it+1})\left[1+(1-\tau_{t+1})\eta^\nu\left(\frac{I_{it+1}}{K_{it+1}}\right)^{\nu-1}\right]}{1+(1-\tau_t)\eta^\nu\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}}. \tag{7}$$

The investment return is the ratio of the marginal benefits of investment at period $t+1$ to the marginal costs of investment at t. The denominator of Equation (7) is the marginal costs of investment, including the marginal purchasing costs (unity) and the marginal adjustment costs, $(1-\tau_t)\eta^\nu(I_{it}/K_{it})^{\nu-1}$. In the numerator, $(1-\tau_{t+1})\kappa Y_{it+1}/K_{it+1}$ is the marginal after-tax profits produced by an additional unit of capital, $(1-\tau_{t+1})(1-1/\nu)(\eta I_{it+1}/K_{it+1})^\nu$ is the marginal after-tax reduction in adjustment costs, $\tau_{t+1}\delta_{it+1}$ is the marginal depreciation tax shield, and the last term in the numerator is the marginal continuation value of the extra unit of capital net of depreciation.

The first-order condition of maximizing Equation (4) with respect to B_{it+1} implies that $E_t[M_{t+1}r^{Ba}_{it+1}]=1$, in which $r^{Ba}_{it+1}\equiv r^B_{it+1}-(r^B_{it+1}-1)\tau_{t+1}$ is the after-tax corporate bond return. Let $r^S_{it+1}\equiv(P_{it+1}+D_{it+1})/P_{it}$ be the stock return and $w_{it}\equiv B_{it+1}/(P_{it}+B_{it+1})$ be the market leverage. Under constant returns to scale, the investment return equals the weighted average of the stock return and the after-tax corporate bond return:

$$r^I_{it+1}=w_{it}r^{Ba}_{it+1}+(1-w_{it})r^S_{it+1}. \tag{8}$$

Equivalently, the stock return equals the levered investment return, denoted r^{Iw}_{it+1}:

$$r^S_{it+1}=r^{Iw}_{it+1}\equiv\frac{r^I_{it+1}-w_{it}r^{Ba}_{it+1}}{1-w_{it}}. \tag{9}$$

2. Econometric Methodology and Sample Construction

Section 2.1 presents our econometric methodology, and Section 2.2 describes our data.

2.1 Econometric methodology

We first describe our GMM methodology and then compare it with existing studies in the investment literature.

2.1.1 Moment conditions. We adopt Tobin's q as the measure of valuation, following the investment literature. We define Tobin's q as $q_{it} \equiv (P_{it} + B_{it+1})/A_{it}$, in which A_{it} is total assets. Using total assets as the denominator of q is standard in empirical finance (e.g., Kaplan and Zingales 1997; Hadlock and Pierce 2010). Based on Equation (5), we test if the average Tobin's q observed in the data equals the average q predicted in the model:

$$E\left[q_{it} - \left(1+(1-\tau_t)\eta^{\nu}\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}\right)\frac{K_{it+1}}{A_{it}}\right]=0. \qquad (10)$$

To construct a formal test, we define the valuation errors from the empirical moments as:

$$e_i^q \equiv E_T\left[q_{it} - \left(1+(1-\tau_t)\eta^{\nu}\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}\right)\frac{K_{it+1}}{A_{it}}\right], \qquad (11)$$

in which $E_T[\cdot]$ is the sample mean of the series in brackets. The key identification assumption for estimation and testing is that the realized valuation errors (the term inside the brackets in Equation [11]) equal zero on average if the model is correctly specified.

To see where the model errors come from, we note that although Equation (5) is an exact relation, measurement errors in variables are likely to invalidate them in practice. Mismeasured components of q_{it} such as the market value of debt and the capital stock can be better observed by firms than by econometricians. The intrinsic value of equity can temporarily diverge from the market value of equity. Finally, adjustment costs in Equation (2) might be misspecified.

We only test the unconditional moments given by Equation (10), instead of the conditional version of the moments that can be transformed into unconditional moments by scaling with instruments known at time t. We do not pursue the conditional estimation because scaling with lagged instruments is not valid in our context. In classical GMM applications in consumption-based asset pricing (e.g., Hansen and Singleton 1982), errors in the moment conditions are forecasting errors. For identification, the standard practice is to invoke rational expectations, meaning that forecasting errors are not forecastable. This assumption validates the scaling of conditional moments with instruments.[3]

[3] This point can also be seen within our setup. Rewriting Equation (4) recursively yields $V_{it} = D_{it} + E_t[M_{t+1} V_{it+1}]$. Equivalently, we have $E_t[M_{t+1} r^S_{it+1}] = 1$, in which $r^S_{it+1} = (P_{it+1} + D_{it+1})/P_{it} = V_{it+1}/(V_{it} - D_{it})$. As such, the errors, $M_{t+1} r^S_{it+1} - 1$, are not forecastable with any instruments known at time t under rational expectations.

In contrast, the errors in the valuation moments given by Equation (10) are measurement errors (including specification errors) in nature. These errors can be correlated with lagged instruments, especially if these errors are persistent.

Although we focus primarily on valuation, we also test whether the average stock return equals the average levered investment return (jointly with the valuation moments [10]):

$$E\left[r^S_{it+1}-r^{Iw}_{it+1}\right]=0. \tag{12}$$

To a first approximation, stock returns can be viewed as (scaled) first differences of equity value (ignoring current dividends that are a small part of the market equity). As such, estimating the two sets of moments simultaneously allows us to evaluate the model's fit in both the levels and the first differences of asset prices. We define the expected return errors as:

$$e^r_i \equiv E_T\left[r^S_{it+1}-r^{Iw}_{it+1}\right]. \tag{13}$$

The identification assumption is that the realized errors, $r^S_{it+1}-r^{Iw}_{it+1}$, are on average zero. In addition to measurement errors that can invalidate the exact equality of Equation (5), the expected return errors can arise because of additional specification errors. For instance, marginal product of capital might not be proportional to sales-to-capital.

The valuation moment (10) provides a valuation estimate without cash flow forecasts or discount rate estimates. However, the equation allows assets to be misvalued but forces managers to align investment with misvalued q via the first-order condition of investment. To alleviate this concern (and to provide an additional robustness check), we follow Chirinko and Schaller (1996, 2001) in estimating the valuation moment jointly with the investment Euler equation moment specified as:

$$E\left[\left(\begin{array}{c} 1+(1-\tau_t)\eta^\nu\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1} - \\ \dfrac{\left[\begin{array}{c}(1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}}+\frac{\nu-1}{\nu}\left(\eta\frac{I_{it+1}}{K_{it+1}}\right)^\nu\right]+\delta_{it+1}\tau_{t+1} \\ +(1-\delta_{it+1})\left[1+(1-\tau_{t+1})\eta^\nu\left(\frac{I_{it+1}}{K_{it+1}}\right)^{\nu-1}\right]\end{array}\right]}{w_{it}r^{Ba}_{it+1}+(1-w_{it})r^S_{it+1}}\end{array}\right)\frac{K_{it+1}}{A_{it}}\right]=0. \tag{14}$$

Accordingly, we define the (scaled) Euler equation errors, e^e_i, as the finite sample average of the term inside the outer brackets in Equation (14). The moment condition follows directly from Equation (6). We follow Merz and Yashiv (2007) in specifying M_{t+1} as the inverse of the weighted average cost of capital. We scale both sides of the Euler equation by K_{it+1}/A_{it} so that the Euler equation errors, e^e_i, have the same magnitude as the valuation errors, e^q_i, to facilitate the joint estimation.

More important, the level of the market equity does not enter the Euler equation moment (14). In fact, the right-hand side of Equation (6) is exactly the present value of future cash flows generated by one extra unit of capital. The Euler equation requires managers to choose investment such that its marginal costs equal its marginal benefits measured as the present value of incremental cash flows. As such, including the Euler equation moment in our estimation anchors managers' investment decisions on economic fundamentals. While misvaluation is hard to rule out entirely, jointly estimating the valuation moment and the Euler equation moment should at least in principle alleviate the impact of misvaluation on our main results.

2.1.2 GMM estimation and tests. We estimate the parameters, η, ν, and κ, using one-step GMM to minimize a weighted average of e_i^q, a weighted average of both e_i^q and e_i^r, or a weighted average of e_i^q and e_i^e. We use the identity-weighting matrix to preserve the economic structure of the testing portfolios, following Cochrane (1996). However, e_i^q can often be larger than e_i^r by an order of magnitude. As such, when estimating e_i^q and e_i^r jointly, we adjust the weighting matrix such that their weights make the two sets of errors comparable in magnitude. In particular, we multiply the valuation moments by a factor of $\overline{|e_i^r|}/\overline{|e_i^q|}$, in which $\overline{|e_i^q|}$ is the mean absolute valuation error from estimating only the valuation moments across a given set of testing assets (indexed by i), and $\overline{|e_i^r|}$ is the mean absolute return error from estimating only the expected return moments across the same testing assets.

We estimate the parameters, $\mathbf{b} \equiv (\eta, \nu, \kappa)$, by minimizing a weighted combination of the sample moments, denoted by $\mathbf{g}_T$. The GMM objective function is a weighted sum of squares of the model errors, $\mathbf{g}_T' \mathbf{W} \mathbf{g}_T$, in which $\mathbf{W}$ is the (adjusted) identity matrix. Let $\mathbf{D} = \partial \mathbf{g}_T / \partial \mathbf{b}$. We estimate $\mathbf{S}$, a consistent estimate of the variance-covariance matrix of the sample errors $\mathbf{g}_T$, with a standard Bartlett kernel with a lag length of three. The estimate of $\mathbf{b}$, denoted $\hat{\mathbf{b}}$, is asymptotically normal with the variance-covariance matrix: $\text{var}(\hat{\mathbf{b}}) = \frac{1}{T}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\mathbf{S}\mathbf{W}\mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}$. To construct standard errors for individual model errors, we use $\text{var}(\mathbf{g}_T) = \frac{1}{T}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]\mathbf{S}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]'$, which is the variance-covariance matrix for $\mathbf{g}_T$. We follow Hansen (1982), lemma 4.1) to form a χ^2 test on the null that all of the model errors are jointly zero: $\mathbf{g}_T' [\text{var}(\mathbf{g}_T)]^+ \mathbf{g}_T \sim \chi^2(\#\text{moments} - \#\text{parameters})$, in which χ^2 denotes the chi-square distribution, and the superscript + denotes pseudo-inversion.

We conduct the estimation and tests at the portfolio level. First, the use of portfolio-level data significantly reduces the impact of the measurement errors in firm-level data that have plagued the empirical performance of the investment regressions. By aggregating the firm-level data to the portfolio level, the impact of measurement errors, such as those related to unobserved firm-level fixed effects, is reduced. Second, because forming portfolios helps diversify residual variances, the valuation (and the expected return) spreads are more reliable statistically across portfolios than across individual stocks.

Finally, investment data at the portfolio level are smoother than those at the firm level, consistent with the smooth adjustment costs function in Equation (2).

2.1.3 Comparison with prior investment studies. Despite its importance, valuation has largely been ignored in prior investment studies. Also, our valuation approach differs from the standard investment regressions in critical ways.

The neoclassical investment theory is originally developed to explain investment behavior, both at the aggregate level and at the firm level (e.g., Jorgenson 1963; Hayashi 1982; Abel 1983). The empirical failure of this theory is well documented in the investment regressions literature (e.g., Fazzari, Hubbard, and Petersen 1988). Testing whether Tobin's q is a sufficient statistic of investment, the investment regressions are performed on Tobin's q, often with cash flows or lagged investment as controls. The investment model is typically rejected because the regressions produce low goodness-of-fit coefficients. Also, cash flows and lagged investment are significant, even with Tobin's q controlled for, whereas q is often insignificant even when used alone.

Our econometric methodology differs from the investment regressions in three aspects. First, as noted, we conduct the estimation and tests at the portfolio level, which mitigates the impact of measurement errors in Tobin's q and other characteristics, errors that are likely responsible for the empirical failure of the investment regressions (e.g., Erickson and Whited 2000). Second, we allow the marginal costs of investment to be nonlinear in the estimation, whereas the standard (albeit not all) investment regressions are derived only under the assumption of linear marginal costs of investment.

Third, we test whether investment is a sufficient statistic for *average* Tobin's q. Focusing only on the first moment alleviates greatly the impact of any timing misalignment between asset prices and investment. The misalignment can arise because investment lags prevent high- and medium-frequency movements in asset prices to be reflected immediately in the investment data (e.g., Lettau and Ludvigson 2002). Also, Tobin's q depends on both existing capital and available technologies yet to be installed, but investment depends only on currently installed technology. As such, Tobin's q is more forward-looking than investment, causing investment to be more responsive to q at long horizons than at short horizons (e.g., Abel and Eberly 2002).

The investment literature has also conducted investment Euler equation tests (e.g., Whited 1992). Our tests based on the valuation moment (10) exploit the information in stock prices data. In contrast, the Euler equation tests use investment and cash flows data only. Our tests also differ from the Merz and Yashiv (2007) tests, which build on a valuation equation equivalent to the investment Euler equation (see also Israelsen 2010). Expressed in our notations, their equation is:

$$P_{it}+B_{it+1}=E_t\left[M_{t+1}\left((1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}}+\frac{\nu-1}{\nu}\left(\eta\frac{I_{it+1}}{K_{it+1}}\right)^{\nu}\right]\right.\right.$$
$$\left.\left.+\,\delta_{it+1}\tau_{t+1}+(1-\delta_{it+1})\left[1+(1-\tau_{t+1})\eta^{\nu}\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}\right]\right)\right]K_{it+1}. \tag{15}$$

In practice, Merz and Yashiv parameterize the marginal product of capital and the stochastic discount factor. As such, their tests must take a stand on the discount rate. In contrast, our main tests are immune to measurement errors in the marginal product of capital and in the discount rate.

2.2 Sample construction

Our sample consists of all common stocks on NYSE, Amex, and Nasdaq from 1963 to 2011. The firm-level data are from the Center for Research in Security Prices (CRSP) monthly stock files and the annual Standard and Poor's Compustat files. We delete firm-year observations for which total assets, capital, or sales are either zero or negative. We also exclude firms with primary standard industrial classifications between 4900 and 4949 (utilities) and between 6000 and 6999 (financials).

2.2.1 Portfolio definitions. We use ten deciles formed on Tobin's q as the benchmark testing portfolios. The q deciles by construction exhibit the largest possible spread in q in the cross-section so as to increase the power of the tests. Following the timing convention in Fama and French (1993), we sort all stocks on Tobin's q at the end of June of year t into deciles based on the NYSE-Amex-NASDAQ breakpoints. We calculate equal-weighted annual returns from July of each year t to June of year $t+1$ for the portfolios, which are rebalanced at the end of each June. We use equal-weighted returns because these returns represent a higher hurdle for asset-pricing models to explain.

We compute the sorting variable, $q_{it}=(P_{it}+B_{it+1})/A_{it}$, at the end of June of year t as follows. The denominator, A_{it}, is total assets (Compustat annual item AT) for the fiscal year ending in calendar year $t-1$. The market value of equity, P_{it}, is the stock price per share (CRSP item prc) times the number of shares outstanding (CRSP item shrout) observed at the end of June of year t. Using the most up-to-date information on the market equity in the sorts increases the spread in q across the deciles. The value of debt, B_{it+1}, is long-term debt (Compustat annual item DLTT) plus short-term debt (item DLC) for the fiscal year ending in calendar year $t-1$. The timing in the model is such that B_{it} is paid off and B_{it+1} is issued at the beginning of t. As such, B_{it+1} is the amount of debt over the course of period t. Also, we calculate the stock returns across the q deciles in the expected return moments. As such, using debt for the fiscal year ending in calendar year t, which is not available prior to the portfolio formation at the end of June of t, is not appropriate due to look-ahead bias.

2.2.2 Variable measurement and timing alignment. We largely follow Liu, Whited, and Zhang (2009) in measuring accounting variables and in aligning their timing with the timing of stock returns at the portfolio level. We make three adjustments, however. First, we measure the capital stock, K_{it}, as net property, plant, and equipment (PPE, Compustat annual item PPENT), as opposed to gross PPE. Net PPE is more consistent with the capital accumulation Equation (1), in which K_{it+1} is defined as net of capital depreciation, $\delta_{it}K_{it}$. Second, we include all the firms with fiscal year ending in the second half of the calendar year, as opposed to only firms with fiscal year ending in December. This adjustment enlarges the sample substantially. Finally, we equal-weight (as opposed to value-weight) corporate bond returns for the testing portfolios to make the weighting of bond returns consistent with that of stock returns.

Investment, I_{it}, is capital expenditures (Compustat annual item CAPX) minus sales of property, plant, and equipment (item SPPE if available). The capital depreciation rate, δ_{it}, is the amount of depreciation (item DP) divided by the capital stock, K_{it}. Output, Y_{it}, is sales (item SALE). Market leverage, w_{it}, is the ratio of total debt to the sum of total debt and the market value of equity. We measure the tax rate, τ_t, as the statutory corporate income tax (from the Commerce Clearing House, annual publications). The after-tax corporate bond returns, r^{Ba}_{it+1}, are computed from r^{B}_{it+1} using the average of tax rates in year t and $t+1$. For the pre-tax corporate bond returns, r^{B}_{it+1}, we follow Blume, Lim, and MacKinlay (1998) to impute the credit ratings for firms with no rating data from Compustat (item SPLTICRM), and then assign the corporate bond returns for a given credit rating from Ibbotson Associates to all the firms with the same credit rating.[4]

Compustat records both stock and flow variables at the end of year t. In the model, however, stock variables dated t are measured at the beginning of year t, and flow variables dated t are over the course of year t. To capture this timing difference, we take, for example, for the year 2003 the beginning-of-year capital, K_{i2003}, from the 2002 balance sheet and any flow variable over the year, such as I_{i2003}, from the 2003 income or cash flow statement. In particular, to match with q_{it} for portfolios formed at the end of June of year t, we take

[4] In particular, we first estimate an ordered probit model that relates credit ratings to observed explanatory variables using all the firms that have credit ratings data. We then use the fitted value to calculate the cutoff value for each credit rating. For firms without credit ratings we estimate their credit scores using the coefficients estimated from the ordered probit model and impute credit ratings by applying the cutoff values of different credit ratings. Finally, we assign the corporate bond returns for a given credit rating from Ibbotson Associates to all the firms with the same credit rating. The ordered probit model contains the following explanatory variables: interest coverage, the ratio of operating income after depreciation (Compustat annual item OIADP) plus interest expense (item XINT) to interest expense; the operating margin, the ratio of operating income before depreciation (item OIBDP) to sales (item SALE), long-term leverage, the ratio of long-term debt (item DLTT) to assets (item AT); total leverage, the ratio of long-term debt plus debt in current liabilities (item DLC) plus short-term borrowing (item BAST) to assets; the natural logarithm of the market value of equity (item PRCC_C times item CSHO) deflated to 1973 by the consumer price index; and the market beta and residual volatility from the market regression. We estimate the beta and residual volatility for each firm in each calendar year with at least 200 daily returns from CRSP. We adjust for nonsynchronous trading with one leading and one lagged values of the market return.

I_{it} from the fiscal year ending in calendar year t and K_{it} from the fiscal year ending in year $t-1$.

We aggregate firm-level characteristics to portfolio-level characteristics as in Fama and French (1995). For example, Y_{it+1}/K_{it+1} is the sum of sales in year $t+1$ for all the firms in portfolio i formed in June of year t divided by the sum of capital stocks at the beginning of year $t+1$ for the same set of firms. I_{it+1}/K_{it+1} in the numerator of r^I_{it+1} is the sum of investment in year $t+1$ for all the firms in portfolio i formed in June of year t divided by the sum of capital stocks at the beginning of year $t+1$ for the same set of firms. I_{it}/K_{it} in the denominator of r^I_{it+1} is the sum of investment in year t for all the firms in portfolio i formed in June of year t divided by the sum of capital stocks at the beginning of year t for the same set of firms. Because the firm composition of portfolio i changes from year to year due to annual rebalancing, I_{it+1}/K_{it+1} in the numerator of r^I_{it+1} is different from I_{it+1}/K_{it+1} in the denominator of r^I_{it+2}. Other characteristics are aggregated analogously.

To match levered investment returns with stock returns, we need to align their timing. As noted, we use the Fama-French portfolio approach in forming testing portfolios at the end of June of each year t. Portfolio stock returns are calculated from July of year t to June of year $t+1$. To construct the matching annual investment returns, we use capital at the end of fiscal year $t-1$ (K_{it}), the tax rate, investment, and capital at the end of year t (τ_t, I_{it}, and K_{it+1}), as well as other variables at the end of year $t+1$ ($\tau_{t+1}, Y_{it+1}, I_{it+1}$, and δ_{it+1}). Because stock variables are measured at the beginning of the year and because flow variables are realized over the course of the year, the investment returns go (approximately) from the middle of year t to the middle of year $t+1$. As such, the investment return timing largely matches the stock return timing.

3. Empirical Results

Section 3.1 reports the estimation results across the Tobin's q deciles. Section 3.2 analyzes subsamples split by firm characteristics. Sections 3.3 and 3.4 report the joint estimation of the valuation moment and the expected return moment as well as the joint estimation of the valuation moment and the Euler equation moment, respectively. In Section 3.5, we stress-test the model by fitting the valuation moment across more disaggregated q portfolios and quantify the importance of the curvature parameter. Finally, Section 3.6 conducts industry-specific estimation.[5]

3.1 GMM estimation and tests

Panel A of Table 1 reports the firm-level descriptive statistics of the sample for matching the valuation moments across the Tobin's q deciles. The sample

[5] The Internet Appendix contains supplementary results including parameter stability tests, specification tests by including conditioning variable such as cash flows and lagged investment into the valuation moment (10), and tests on alternative testing portfolios formed on market-to-book, asset growth, and return on equity.

Table 1
Firm-level and portfolio-level descriptive statistics of the sample for matching the valuation moments across the Tobin's q deciles, 1963–2011

Panel A: Firm-level descriptive statistics

	Mean	Std	Skewness	5%	25%	50%	75%	95%
q_{it}	1.72	2.39	8.03	0.48	0.77	1.10	1.79	4.81
$\frac{I_{it}}{K_{it}}$	0.35	1.67	17.06	0.01	0.11	0.20	0.37	0.97
$\frac{K_{it+1}}{A_{it}}$	0.36	0.31	4.55	0.06	0.17	0.29	0.49	0.87

Panel B: Portfolio-level descriptive statistics across the Tobin's q deciles

	Mean	Low	2	3	4	5	6	7	8	9	High	H–L	[t]
q_{it}	1.56	0.44	0.65	0.77	0.89	1.02	1.19	1.43	1.80	2.52	4.94	4.50	12.11
$\frac{I_{it}}{K_{it}}$	0.22	0.15	0.16	0.16	0.17	0.18	0.20	0.22	0.25	0.29	0.39	0.24	14.70
$\frac{K_{it+1}}{A_{it}}$	0.43	0.30	0.40	0.44	0.46	0.48	0.49	0.49	0.47	0.41	0.40	0.10	3.44

Panel A reports firm-level statistics including mean, standard deviation (Std), skewness, as well as the 5th, 25th, 50th, 75th, and 95th percentiles for Tobin's q, q_{it}; investment-to-capital, I_{it}/K_{it}; and next period capital-to-assets, K_{it+1}/A_{it}. Panel B reports the time series averages of these variables for each of the Tobin's q deciles, the averages of these averages across the deciles, the differences between the high- and the low-q deciles, and the t-statistics testing that the differences are on average equal to zero.

is from 1963 to 2011, and the average number of firms in the cross-section is 2,291. Both Tobin's q and investment-to-capital are highly skewed, with skewness 8.03 and 17.06, respectively. The mean q is 1.72, which is higher than the median of 1.10, and the standard deviation is 2.39. The mean investment-to-capital ratio is 0.35, which is higher than the median of 0.20, and its standard deviation is 1.67. The high skewness would affect the precision of standard investment regressions at the firm level, but its impact is mitigated in our test design by aggregating the data at the portfolio level.

Panel B of Table 1 reports the portfolio-level descriptive statistics across the q deciles. Tobin's q varies from 0.44 for the low decile to 4.94 for the high decile. We define the valuation spread as the Tobin's q of the high decile minus that of the low decile. As such, sorting on q produces a large valuation spread of 4.5, which is more than 12 standard errors from zero. Going in the right direction to match the valuation spread, the high decile also has a higher investment-to-capital ratio than the low decile, 0.39 versus 0.15, and a higher next period capital-to-assets ratio, 0.40 versus 0.30.

Table 2 reports the point estimates and overall performance of the investment model using the valuation moments given by Equation (10) across the Tobin's q deciles. There are only two parameters in the valuation moments, the slope parameter, η, and the curvature parameter, ν, in the adjustment costs function. From Panel A, the η estimate is 4.15, and is highly significant. The ν estimate is 3.75, which is also significantly positive. In addition, the ν estimate is significantly different from two based on a Wald test. The evidence suggests that the adjustment costs function in the data exhibits more curvature than the standard quadratic functional form. The point estimates of η and ν also imply that adjustment costs are increasing and convex in investment-to-capital.

Table 2
GMM estimation and tests for the Tobin's q deciles, 1963–2011

Panel A: Point estimates and the χ^2 tests

η	$[t]$	ν	$[t]$	$p_{\nu=2}$	Φ/Y	$\overline{\|e_i^q\|}$	χ^2	d.f.	p_{χ^2}
4.15	18.64	3.75	18.62	0.00	4.78	0.07	7.63	8	0.47

Panel B: Valuation errors for individual deciles

	Low	2	3	4	5	6	7	8	9	High	H–L
e_i^q	−0.10	−0.11	−0.06	−0.03	−0.05	−0.03	0.01	−0.05	0.24	−0.05	0.05
$[t]$	−1.77	−2.18	−1.49	−0.90	−1.20	−0.93	0.23	−0.80	1.83	−1.88	1.21

Panel A reports the results via one-step GMM on the valuation moments given by Equation (10), using the Tobin's q deciles as the testing portfolios. There are two parameters: η is the slope, and ν is the curvature of the adjustment costs function. The t-statistics, denoted $[t]$, test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{|e_i^q|}$ is the mean absolute valuation error. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that all the errors are jointly zero. Panel B reports for each individual decile and the high-minus-low decile the valuation errors defined in Equation (11) and their t-statistics.

To interpret the magnitude of the adjustment costs, we report the implied proportion of lost sales due to adjustment costs, denoted Φ/Y. We calculate this ratio by (i) aggregating all the investment, capital, and sales across all the firms in the economy for each year in the sample; (ii) computing the time series of the adjustment costs by plugging these aggregates into Equation (2); and (iii) taking the average of the adjustment costs-to-sales ratio in the time series. From Panel A, the estimated magnitude of the adjustment costs is about 4.78% of sales. This estimate is largely in line with prior studies. For example, Bloom (2009, Table IV) surveys the estimates of convex adjustment costs to be between zero and 20% of revenue, depending on the variety of data, model specifications, and econometric techniques adopted in different studies.

Table 2 also reports two overall performance measures, the mean absolute valuation error, $\overline{|e_i^q|}$, and the χ^2 test. As noted, $\overline{|e_i^q|}$ is the mean of the absolute valuation errors given by Equation (11) across a set of testing portfolios. This metric shows that the model performs well in matching Tobin's q. From Panel A, $\overline{|e_i^q|}$ is only 0.07, which represents about 4.5% of the average q across the deciles (1.56, see Table 1). Also, the model is not rejected by the χ^2 test with a p-value of 47%.

The mean absolute error and the χ^2 test only indicate overall model performance. To provide a more complete picture of the fit, Panel B of Table 2 reports the valuation errors, e_i^q, for all the individual deciles and their corresponding t-statistics. The errors range in magnitude from 0.01 to 0.24. Only one out of ten deciles has an error significant at the 5% level. The high-minus-low decile has a small error of 0.05 ($t=1.21$), which is only about 1.1% of the valuation spread of 4.5.

Figure 1 illustrates the model's fit by plotting the predicted q against the realized q across the Tobin's q deciles. If the model's fit is perfect, all the

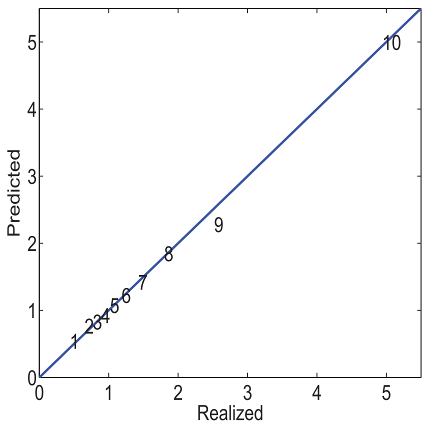

Figure 1
Average predicted q versus average realized q, the Tobin's q deciles, 1963–2011
The results are from estimating the investment model via one-step GMM using the valuation moment given by Equation (10). The test assets are the Tobin's q deciles, which are labeled in an ascending order.

scattered points should lie exactly on the 45-degree line. The figure shows that the scattered points are largely aligned with the 45-degree line. As such, the investment model seems to do a good job in matching Tobin's q across the q deciles.

To get a sense of the magnitude of measurement errors in q, we calculate time series correlations between the predicted q and the realized q, both in levels and in changes. A less than perfect correlation would indicate measurement errors. The time series correlation in levels varies from -0.29 for the seventh q decile to 0.59 for the low q decile. Pooling all the time series observations together across all ten deciles, we compute the correlation to be 0.58. (However, this estimate also reflects cross-sectional correlation.) In addition, the time series correlation between the change in the predicted q and the change in the realized q varies from -0.04 for the seventh decile to 0.49 for the high q decile. Pooling across all ten deciles, this correlation is 0.47. The low correlations suggest large measurement errors, which are likely responsible for the failure of q-theory in the investment regressions. As such, the evidence lends support to our approach of focusing on the first moment of q, which is immune to the influence of measurement errors (with a mean of zero).

Finally, in the Internet Appendix, we also document that the parameter estimates are stable over time in subsample analysis, rolling-window estimation, and tests with time-varying parameters.

3.2 Tests on subsamples split by firm characteristics

As noted, cash flows, and more generally, financial constraints can cause q-theory to fail in the context of the investment regressions. In addition, Eberly, Rebelo, and Vincent (2012) show that the best predictor of current investment at the firm level is lagged investment and suggest that a specification of investment (as opposed to capital) adjustment costs can account for this evidence. Panousi and Papanikolaou (2012) show that idiosyncratic volatility affects investment after controlling for Tobin's q. Although our objective is not to fix the investment regressions, it seems worthwhile to quantify to what extent our econometric design can handle the classical rejections of q-theory. To this end, we split the sample into terciles based on these characteristics, and then fit our model on the Tobin's q deciles within each subsample.

To measure financial constraints, we use the Hadlock and Pierce (2010) size-age (SA) index. Their SA index is calculated as $-0.737\times\text{size}+0.043\times\text{size}^2-0.040\times\text{age}$, in which size is the log of inflation-adjusted book assets (Compustat annual item AT), and age is the number of years that the firm has been on Compustat with a non-missing stock price. We replace size with log($4.5 billion) and age with 37 years if the actual values exceed these thresholds.

Following Panousi and Papanikolaou (2012), we measure idiosyncratic volatility using weekly stock returns from CRSP. For each firm at the end of June of each year t, we regress the firm's weekly excess returns from July of year $t-1$ to June of t on the value-weighted market excess returns and on the value-weighted industry excess returns per the Fama-French (1997) 30-industry classification. We require a minimum of 40 weekly observations. The firm's idiosyncratic volatility is calculated as the logarithm of the volatility of the residual returns. Finally, we measure cash flows as earnings before extraordinary items (Compustat annual item IB) plus depreciation and amortization (item DP), scaled by lagged capital (item PPENT).

At the end of June of each year t, we split the sample into terciles based on each stock's SA index value for the fiscal year ending in calendar year $t-1$, idiosyncratic volatility calculated at the end of June of year t, as well as cash flows and investment-to-capital for the fiscal year ending in year $t-1$. Within each tercile, we sequentially sort stocks into deciles based on Tobin's q. The timing of q_{it} in the sorts is identical to that in the benchmark tests in Table 2 (see Section 2.2.1 for the timing description). We then fit the investment model on the Tobin's q deciles within each subsample.

Table 3 reports the results on subsamples split by the SA index. From Panel A, the valuation spread across the q deciles is higher in the high SA tercile (most constrained) than in the low SA tercile (least constrained): 8.23 versus 3.11. The average q across the deciles is also higher in the high SA tercile: 2.30 versus 1.28. Going in the right direction to match q, the investment-to-capital spread across the q deciles is higher in the high SA tercile: 0.60 versus 0.16. From Panel B, the model seems to fit well overall. The largest mean absolute valuation error is 0.18 in the high SA tercile but is only about 7.83% of the average q across the q deciles. The error is only 0.04 in the low SA tercile, which is about 3.23% of the average q. Panel C shows that the high-minus-low error is also higher in the high SA tercile, 0.20 versus 0.04 but is more comparable as

Table 3
GMM estimation and tests for the Tobin's q deciles, subsamples split by the Hadlock-Pierce (2010) SA index of financial constraints, 1963–2011

Panel A: Descriptive statistics

	Mean	Low	2	3	4	5	6	7	8	9	High	H–L	[t]
Low SA (least constrained)													
q_{it}	1.28	0.44	0.64	0.75	0.85	0.95	1.07	1.23	1.45	1.88	3.55	3.11	14.17
$\frac{I_{it}}{K_{it}}$	0.20	0.15	0.17	0.16	0.17	0.18	0.18	0.20	0.22	0.24	0.31	0.16	14.77
$\frac{K_{it+1}}{A_{it}}$	0.44	0.30	0.39	0.45	0.47	0.48	0.50	0.49	0.48	0.44	0.41	0.11	3.93
Median SA													
q_{it}	1.49	0.41	0.63	0.75	0.86	0.98	1.13	1.34	1.65	2.26	4.86	4.45	9.30
$\frac{I_{it}}{K_{it}}$	0.25	0.15	0.16	0.17	0.18	0.22	0.23	0.25	0.29	0.37	0.52	0.37	7.97
$\frac{K_{it+1}}{A_{it}}$	0.41	0.29	0.35	0.38	0.45	0.43	0.45	0.46	0.45	0.42	0.41	0.12	4.49
High SA (most constrained)													
q_{it}	2.30	0.48	0.70	0.87	1.05	1.27	1.55	1.98	2.63	3.81	8.71	8.23	7.43
$\frac{I_{it}}{K_{it}}$	0.36	0.17	0.18	0.21	0.24	0.30	0.32	0.39	0.49	0.56	0.77	0.60	10.14
$\frac{K_{it+1}}{A_{it}}$	0.33	0.28	0.30	0.33	0.33	0.33	0.34	0.34	0.35	0.35	0.39	0.11	5.24

Panel B: Point estimates and the χ^2 tests

	η	[t]	ν	[t]	$p_{\nu=2}$	Φ/Y	$\overline{\lvert e_i^q \rvert}$	χ^2	d.f.	p_{χ^2}
Low SA	4.19	19.90	4.39	24.71	0.00	3.65	0.04	8.16	8	0.42
2	3.61	23.71	3.12	16.67	0.00	5.95	0.05	8.93	8	0.35
High SA	3.39	11.55	3.22	17.37	0.00	9.21	0.18	8.53	8	0.38

Panel C: Valuation errors for individual deciles

	Low	2	3	4	5	6	7	8	9	High	H–L
Low SA (least constrained)											
e_i^q	−0.05	−0.11	−0.01	−0.04	0.01	0.07	−0.02	−0.01	0.07	−0.01	0.04
[t]	−1.18	−2.28	−0.39	−1.07	0.36	1.77	−0.42	−0.33	1.02	−0.85	0.90
Median SA											
e_i^q	−0.04	0.04	0.09	−0.04	−0.07	−0.06	−0.01	−0.02	0.09	−0.01	0.03
[t]	−1.45	0.96	1.95	−0.69	−0.65	−0.61	−0.08	−0.27	0.60	−0.45	1.55
High SA (most constrained)											
e_i^q	−0.06	0.18	0.14	0.23	0.03	0.28	0.18	−0.32	−0.30	0.15	0.20
[t]	−0.77	2.01	1.06	1.66	0.11	1.32	1.22	−1.38	−0.75	1.00	1.25

At the end of June of year t, we split the sample into terciles based on the Hadlock and Pierce (2010) SA index for the fiscal year ending in calendar year $t-1$. Within each SA tercile, we sort stocks into deciles on Tobin's q. For each q decile, Panel A reports the time series averages of Tobin's q, q_{it}; investment-to-capital, I_{it}/K_{it}; and capital-to-assets, K_{it+1}/A_{it}, as well as the averages of these averages across the deciles, Mean; and the differences between the extreme deciles, and their t-statistics within a given tercile. Panel B reports for each SA tercile the estimation results via one-step GMM on the valuation moments given by Equation (10), using the q deciles as the testing assets. η is the slope, and ν is the curvature of the adjustment costs function. The t-statistics, denoted [t], test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{|e_i^q|}$ is the mean absolute valuation error. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that the errors are jointly zero across all the deciles within a given SA tercile. Panel C reports the valuation errors and their t-statistics for all the individual deciles.

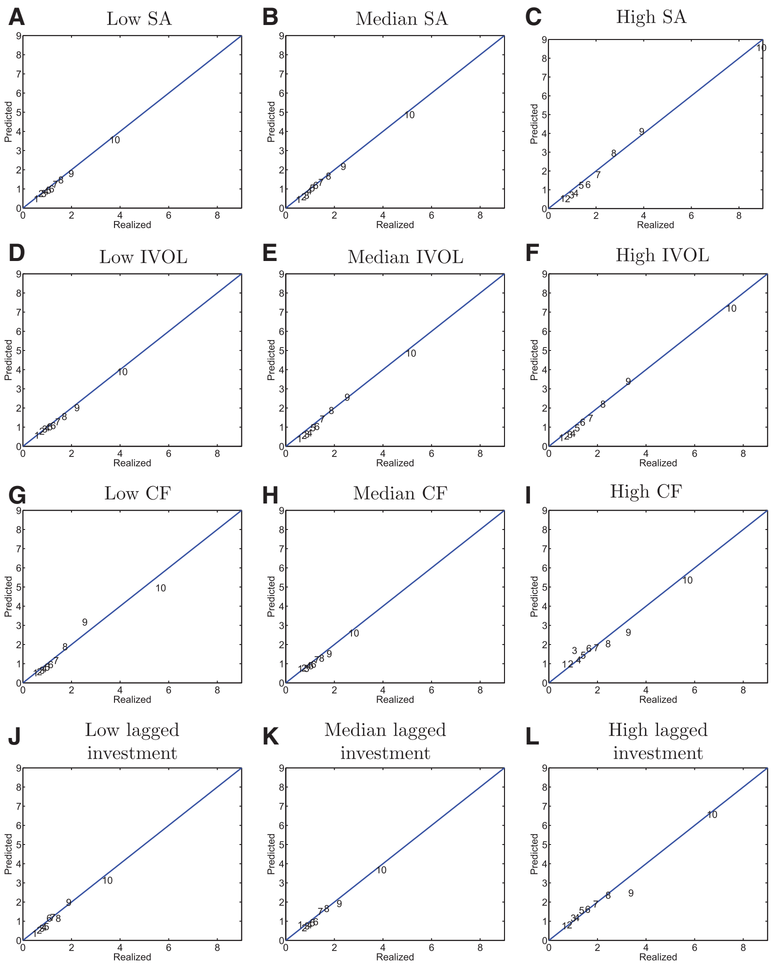

Figure 2
Average predicted *q* versus average realized *q*, the Tobin's *q* deciles, split-sample analysis, 1963–2011
The results are from one-step GMM using the valuation moment given by Equation (10). The testing portfolios are the Tobin's *q* deciles, labeled in an ascending order, within each terciles formed on the size-age index (SA), idiosyncratic volatility (IVOL), cash flows (CF), and lagged investment.

a percentage of the respective valuation spread, 2.43% versus 1.29%. Finally, from Panels A to C in Figure 2, the predicted *q* and the realized *q* are aligned along the 45-degree line.

Table 4 reports the results on subsamples split by idiosyncratic volatility. The valuation spread is higher in the high-volatility tercile than in the low-volatility tercile: 6.88 versus 3.40. Going in the right direction, the investment-to-capital spread is also higher in the high-volatility tercile: 0.67 versus 0.15. From Panel B, the mean absolute valuation errors vary from 0.07 to 0.12, which are about 5–6.5% of the average q across the testing portfolios. The implied adjustment costs range from 3.27% to 4.66% of sales. Panel C also reports small valuation errors for individual deciles. The largest high-minus-low error, 0.13, in the high-volatility tercile is only 1.89% of the valuation spread. Panels D to F in Figure 2 confirm the good fit on the volatility subsamples.

Table 5 reports the results across subsamples split by cash flows. From Panel A, the valuation spread is 5.04, 2.09, and 4.95, and the investment-to-capital spread is 0.31, 0.08, and 0.15 across the low, median, and high terciles, respectively. Panel B shows that the mean absolute errors range from 0.09 to 0.28, which are about 7.83% to 14.74% of the average q within a given subsample. Panel C shows further that the high-minus-low errors vary from 0.23 to 0.61 and are about 11% to 12.1% of the valuation spread within a tercile. Although the valuation errors are somewhat larger than those across the SA and the volatility subsamples, Panels G to I in Figure 2 show that the predicted q and the realized q are again largely aligned with the 45-degree line.

Table 6 reports the results across subsamples split by lagged investment, I_{it-1}/K_{it-1}.[6] The valuation spread ranges from 2.88 to 5.97 and the (current) investment-to-capital spread from 0.09 to 0.31, as we move from the low to the high lagged investment subsample (Panel A). The mean absolute errors vary from 0.11 to 0.21, which are about 8.09% to 10.61% of the average q within a tercile (Panel B). The high-minus-low error is 0.16 in the high lagged investment tercile and is only 2.68% of its valuation spread (Panel C). Panels J to L in Figure 2 again confirm the good fit.

Overall, the model's performance is reasonable in that the valuation errors are in general small. However, the performance is by no means perfect. The implied adjustment costs can occasionally be large. The adjustment costs amount to 9.21% of sales in the high SA tercile, 15.01% in the high cash flows tercile, and 10.32% in the high lagged investment tercile. Although all fall within the range of prior estimates per Bloom (2009), these estimates seem large. We interpret the evidence as indicating possible specification errors. Apart from the nonquadratic adjustment costs, our model is in effect the standard q-theory of investment. The evidence suggests that incorporating financial constraints and investment adjustment costs might improve the model's performance further.

3.3 Matching the valuation moment and the expected return moment jointly

To make sure that the model's fit on the valuation moment is achieved without leading to a bad fit on expected returns, we conduct the joint estimation of the valuation moment (10) and the expected return moment (12) across the Tobin's q deciles. Constructing the expected return moment requires

6 Although the timing of investment in splitting the sample is identical to that of cash flows in Table 5, we call it lagged investment to distinguish it from the current investment, I_{it}/K_{it}, which appears in the valuation moment (10).

Table 4
GMM estimation and tests for the Tobin's q deciles, subsamples split by idiosyncratic volatility (IVOL), 1963–2011

Panel A: Descriptive statistics

	Mean	Low	2	3	4	5	6	7	8	9	High	H–L	[t]
Low IVOL													
q_{it}	1.39	0.46	0.67	0.79	0.89	1.00	1.14	1.33	1.60	2.12	3.86	3.40	16.49
$\frac{I_{it}}{K_{it}}$	0.20	0.16	0.17	0.16	0.17	0.18	0.19	0.20	0.22	0.25	0.32	0.15	11.57
$\frac{K_{it+1}}{A_{it}}$	0.45	0.32	0.41	0.46	0.49	0.50	0.50	0.49	0.47	0.43	0.41	0.08	2.90
Median IVOL													
q_{it}	1.54	0.45	0.65	0.76	0.88	1.01	1.17	1.40	1.77	2.42	4.92	4.47	10.42
$\frac{I_{it}}{K_{it}}$	0.26	0.13	0.15	0.17	0.19	0.22	0.23	0.27	0.32	0.38	0.51	0.38	10.63
$\frac{K_{it+1}}{A_{it}}$	0.41	0.31	0.39	0.41	0.40	0.44	0.44	0.46	0.45	0.42	0.38	0.07	2.35
High IVOL													
q_{it}	1.92	0.40	0.63	0.76	0.89	1.06	1.28	1.61	2.12	3.16	7.28	6.88	7.74
$\frac{I_{it}}{K_{it}}$	0.29	0.11	0.13	0.14	0.15	0.20	0.24	0.28	0.38	0.51	0.78	0.67	9.83
$\frac{K_{it+1}}{A_{it}}$	0.38	0.32	0.33	0.36	0.37	0.40	0.39	0.40	0.42	0.41	0.44	0.12	3.16

Panel B: Point estimates and the χ^2 tests

	η	[t]	ν	[t]	$p_{\nu=2}$	Φ/Y	$\overline{\lvert e_i^q \rvert}$	χ^2	d.f.	p_{χ^2}
Low IVOL	4.22	20.01	4.53	17.04	0.00	3.70	0.07	7.61	8	0.47
2	3.44	21.13	3.67	14.39	0.00	3.27	0.10	9.90	8	0.27
High IVOL	3.61	12.29	2.77	13.77	0.00	4.66	0.12	9.26	8	0.32

Panel C: Valuation errors for individual deciles

	Low	2	3	4	5	6	7	8	9	High	H–L
Low IVOL											
e_i^q	−0.12	−0.11	−0.11	−0.08	−0.02	0.05	0.05	0.04	0.10	−0.03	0.09
[t]	−1.56	−2.06	−0.86	−1.17	−0.33	0.87	1.04	0.77	0.73	−0.87	1.17
Median IVOL											
e_i^q	0.05	0.08	0.13	0.18	0.04	0.14	−0.03	−0.10	−0.14	0.06	0.01
[t]	1.87	1.71	2.37	2.53	0.38	1.86	−0.33	−1.19	−0.71	1.08	0.18
High IVOL											
e_i^q	−0.05	0.09	0.14	0.22	0.10	0.02	0.14	−0.09	−0.23	0.07	0.13
[t]	−1.02	1.41	1.78	1.91	0.85	0.19	0.75	−0.38	−0.57	0.81	1.30

At the end of June of year t, we split the sample into terciles on IVOL. For each firm, we regress its weekly excess returns in the prior year from July of year $t-1$ to June of year t on the value-weighted market excess returns and on the value-weighted industry excess returns per the Fama-French (1997) 30-industry classification. IVOL is the logarithm of the volatility of the residual returns. Within each IVOL tercile, we sort stocks into deciles on Tobin's q. For each q decile, Panel A reports the time series averages of Tobin's q, q_{it}; investment-to-capital, I_{it}/K_{it}; and capital-to-assets, K_{it+1}/A_{it}, as well as the averages of these averages across the deciles, Mean; and the differences between the extreme deciles, and their t-statistics within a given tercile. Panel B reports the one-step GMM estimation on the valuation moments in Equation (10), with the q deciles within each IVOL tercile as the testing assets. η is the slope, and ν is the curvature of the adjustment costs function. The t-statistics, [t], test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{\lvert e_i^q \rvert}$ is the mean absolute valuation error. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that the errors are jointly zero across the q deciles. Panel C reports the valuation errors and their t-statistics.

Table 5
GMM estimation and tests for the Tobin's q deciles, subsamples split by cash flows (CF), 1963–2011

Panel A: Descriptive statistics

	Mean	Low	2	3	4	5	6	7	8	9	High	H–L	[t]
Low CF													
q_{it}	1.51	0.40	0.57	0.68	0.78	0.89	1.03	1.26	1.62	2.44	5.44	5.04	6.63
$\frac{I_{it}}{K_{it}}$	0.18	0.11	0.10	0.11	0.12	0.13	0.16	0.18	0.21	0.29	0.42	0.31	7.12
$\frac{K_{it+1}}{A_{it}}$	0.54	0.42	0.50	0.52	0.56	0.58	0.59	0.58	0.60	0.54	0.51	0.09	2.48
Median CF													
q_{it}	1.15	0.48	0.65	0.75	0.83	0.93	1.03	1.17	1.37	1.68	2.57	2.09	19.88
$\frac{I_{it}}{K_{it}}$	0.21	0.19	0.20	0.18	0.19	0.19	0.20	0.21	0.22	0.23	0.27	0.08	6.43
$\frac{K_{it+1}}{A_{it}}$	0.47	0.35	0.37	0.41	0.44	0.46	0.50	0.52	0.52	0.54	0.58	0.22	12.28
High CF													
q_{it}	1.90	0.52	0.79	0.95	1.11	1.30	1.54	1.85	2.33	3.16	5.48	4.95	14.94
$\frac{I_{it}}{K_{it}}$	0.30	0.27	0.27	0.29	0.27	0.28	0.29	0.29	0.30	0.33	0.41	0.15	9.14
$\frac{K_{it+1}}{A_{it}}$	0.26	0.16	0.18	0.20	0.22	0.25	0.27	0.29	0.30	0.34	0.37	0.20	13.33

Panel B: Point estimates and the χ^2 tests

	η	[t]	ν	[t]	$p_{\nu=2}$	Φ/Y	$\overline{\lvert e_i^q \rvert}$	χ^2	d.f.	p_{χ^2}
Low CF	3.65	12.51	3.61	26.11	0.00	1.90	0.19	10.83	8	0.21
2	3.82	17.77	4.49	9.54	0.00	3.29	0.09	10.74	8	0.22
High CF	4.25	16.46	3.69	9.24	0.00	15.01	0.28	9.76	8	0.28

Panel C: Valuation errors for individual deciles

	Low	2	3	4	5	6	7	8	9	High	H–L
Low CF											
e_i^q	−0.12	−0.01	0.02	0.04	0.07	0.08	0.09	−0.26	−0.73	0.49	0.61
[t]	−1.98	−0.33	0.46	0.58	1.05	1.02	1.04	−0.89	−0.92	0.94	1.20
Median CF											
e_i^q	−0.26	−0.12	−0.01	−0.06	0.03	0.07	−0.04	0.08	0.16	−0.03	0.23
[t]	−2.83	−2.18	−0.15	−1.33	0.78	1.52	−0.87	1.12	2.03	−1.54	2.80
HighCF											
e_i^q	−0.45	−0.20	−0.74	−0.08	−0.14	−0.26	0.01	0.28	0.53	0.11	0.56
[t]	−2.53	−2.45	−1.35	−0.76	−0.94	−1.74	0.09	1.83	2.31	1.08	2.87

At the end of June of year t, we split the sample into terciles based on CF, calculated as earnings before extraordinary items (Compustat annual item IB) plus depreciation and amortization (item DP) for the fiscal year ending in calendar year $t-1$, scaled by net property, plant, and equipment (item PPENT) for the fiscal year ending in year $t-2$. Within each CF tercile, we sort stocks into deciles on Tobin's q. For each q decile, Panel A reports the time series averages of Tobin's q, q_{it}; investment-to-capital, I_{it}/K_{it}; and capital-to-assets, K_{it+1}/A_{it}, as well as the averages of these averages across the deciles, Mean; and the differences between the extreme deciles, and their t-statistics within a given tercile. Panel B reports for each CF tercile the one-step GMM results on the valuation moments in Equation (10), with the q deciles as the testing assets. η is the slope, and ν is the curvature of the adjustment costs function. The t-statistics, [t], test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{\lvert e_i^q \rvert}$ is the mean absolute valuation error. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that the errors are jointly zero across all the deciles within a given CF tercile. Panel C reports the valuation errors and their t-statistics.

Table 6
GMM estimation and tests for the Tobin's q deciles, subsamples split by lagged investment, 1963–2011

Panel A: Descriptive statistics

	Mean	Low	2	3	4	5	6	7	8	9	High	H–L	[t]
Low lagged investment													
q_{it}	1.17	0.37	0.57	0.67	0.76	0.86	0.97	1.12	1.35	1.78	3.25	2.88	13.05
$\frac{I_{it}}{K_{it}}$	0.12	0.08	0.10	0.10	0.11	0.11	0.12	0.13	0.14	0.15	0.17	0.09	9.03
$\frac{K_{it+1}}{A_{it}}$	0.46	0.31	0.44	0.50	0.50	0.48	0.51	0.52	0.49	0.49	0.41	0.10	2.71
Median lagged investment													
q_{it}	1.36	0.48	0.66	0.77	0.87	0.99	1.12	1.31	1.57	2.09	3.70	3.22	13.33
$\frac{I_{it}}{K_{it}}$	0.20	0.19	0.19	0.18	0.19	0.19	0.20	0.21	0.21	0.23	0.25	0.06	7.23
$\frac{K_{it+1}}{A_{it}}$	0.43	0.34	0.36	0.42	0.46	0.46	0.48	0.50	0.48	0.42	0.37	0.03	1.45
High lagged investment													
q_{it}	1.98	0.52	0.74	0.89	1.05	1.24	1.49	1.82	2.33	3.27	6.49	5.97	9.08
$\frac{I_{it}}{K_{it}}$	0.36	0.28	0.27	0.30	0.31	0.34	0.35	0.37	0.40	0.43	0.59	0.31	7.71
$\frac{K_{it+1}}{A_{it}}$	0.40	0.30	0.36	0.39	0.41	0.41	0.44	0.43	0.42	0.41	0.40	0.10	5.23

Panel B: Point estimates and the χ^2 tests

	η	[t]	ν	[t]	$p_{\nu=2}$	Φ/Y	$\overline{\lvert e_i^q \rvert}$	χ^2	d.f.	p_{χ^2}
Low $\frac{I_{it-1}}{K_{it-1}}$	5.51	19.84	6.16	7.29	0.00	0.93	0.11	8.98	8	0.34
2	4.22	41.31	8.70	7.93	0.00	1.38	0.11	8.42	8	0.39
High $\frac{I_{it-1}}{K_{it-1}}$	3.13	23.60	3.82	12.23	0.00	10.32	0.21	9.59	8	0.29

Panel C: Valuation errors for individual deciles

	Low	2	3	4	5	6	7	8	9	High	H–L
Low lagged investment											
e_i^q	0.01	0.03	0.04	0.07	0.14	−0.19	−0.08	0.20	−0.21	0.11	0.11
[t]	0.14	0.77	0.63	1.00	1.92	−0.78	−0.54	0.97	−0.39	0.55	0.55
Median lagged investment											
e_i^q	−0.34	0.00	0.01	0.07	0.06	0.15	−0.20	−0.09	0.17	0.02	0.36
[t]	−2.01	−0.04	0.17	0.88	0.82	1.48	−1.14	−0.44	1.26	0.77	2.08
High lagged investment											
e_i^q	−0.24	−0.07	−0.27	−0.14	−0.33	−0.13	−0.08	−0.02	0.79	−0.08	0.16
[t]	−1.92	−0.66	−1.65	−1.51	−1.53	−1.10	−0.60	−0.06	2.50	−1.77	1.47

At the end of June of year t, we split the sample into terciles based on lagged investment, I_{it-1}/K_{it-1}, which is capital expenditures (Compustat annual item CAPX) minus sales of property, plant, and equipment if available (item SPPE) for the fiscal year ending in calendar year $t-1$, scaled by capital (item PPENT) for the fiscal year ending in year $t-2$. Within each lagged investment tercile, we sort stocks into deciles on Tobin's q. For each q decile, Panel A reports the time series averages of Tobin's q, q_{it}; (current) investment-to-capital, I_{it}/K_{it}; and capital-to-assets, K_{it+1}/A_{it}, as well as the averages of these averages across the deciles, Mean; and the differences between the extreme deciles, and their t-statistics within a given tercile. Panel B reports the one-step GMM estimation on the valuation moments in Equation (10), with the q deciles within each lagged investment tercile as the testing assets. η is the slope, and ν is the curvature of the adjustment costs function. The t-statistics, [t], test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{|e_i^q|}$ is the mean absolute valuation error. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that the errors are jointly zero across all the q deciles. Panel C reports the valuation errors and their t-statistics.

Table 7
GMM estimation and tests for the Tobin's *q* deciles, joint estimation of the valuation moment and the expected return moment, 1963–2011

Panel A: Point estimates and the χ^2 tests

η	[t]	ν	[t]	$p_{\nu=2}$	κ	[t]	Φ/Y	$\overline{\lvert e_i^q \rvert}$	$\overline{\lvert e_i^r \rvert}$	χ^2	d.f.	p_{χ^2}
4.07	18.16	4.17	19.58	0.00	0.18	4.96	3.71	0.07	3.60	11.63	17	0.82

Panel B: Valuation errors, expected return errors, and the Carhart alphas

	Low	2	3	4	5	6	7	8	9	High	H–L
e_i^q	−0.14	−0.07	−0.01	0.02	0.00	0.12	0.06	0.09	−0.15	0.07	0.22
[t]	−2.80	−1.57	−0.27	0.54	−0.05	2.12	1.00	1.47	−0.95	1.15	2.38
e_i^r	−3.32	3.99	2.90	−3.23	6.80	−6.52	−4.07	1.47	3.26	0.44	3.75
[t]	−0.58	1.08	0.89	−0.75	1.99	−1.07	−0.97	0.42	0.72	0.10	0.47
α_i^C	6.80	4.03	2.35	1.80	0.70	−0.27	−1.34	−1.23	−1.53	−3.12	−9.92
[t]	4.40	3.35	2.34	2.12	0.87	−0.36	−1.63	−1.50	−1.55	−2.46	−5.36

Panel A reports the one-step GMM results from estimating jointly the valuation moments and the expected return moments given by Equations (10) and (12), respectively. η is the slope, ν is the curvature of the adjustment costs function, and κ is the capital's share. The t-statistics, denoted [t], test that a given parameter equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$. Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{\lvert e_i^q \rvert}$ is the average magnitude of the valuation errors given by Equation (11). $\overline{\lvert e_i^r \rvert}$ is the average magnitude of the expected return errors (in percent per annum) given by Equation (13). χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that all the errors are jointly zero. Panel B reports for each individual decile and the high-minus-low decile the valuation errors, e_i^q; the expected return errors, e_i^r; the Carhart alphas, α_i^C (the annualized intercept from monthly regressions of portfolio returns in excess of the one-month Treasury bill rate on the Carhart [1997] four factors); as well as their t-statistics.

additional data items that are not in the valuation moment, such as next period investment, depreciation, and sales as well as corporate bond returns. As such, we reconstruct our sample for the joint estimation by imposing this more stringent sample selection criterion. Detailed descriptive statistics of the joint estimation sample are provided in the Internet Appendix.

Table 7 reports the joint estimation results. In addition to the slope and the curvature parameters for the adjustment costs, the expected return moment introduces an additional parameter, the capital's share, κ. From Panel A, the η and ν estimates are 4.07 and 4.17, which are close to 4.15 and 3.75, respectively, in the benchmark estimation (see Table 2). The κ estimate is 0.18, and is significantly positive. The implied adjustment costs-to-sales ratio is 3.71%, which is lower than 4.78% in the benchmark estimation. The mean absolute valuation error remains unchanged at 0.07. The mean absolute return error is 3.60% per annum.

Panel B reports the model errors for individual deciles. The valuation errors are again economically small and statistically insignificant across the deciles. The high-minus-low decile has an error of 0.22, which is about 5.82% of the valuation spread, 3.78. Albeit not large economically, this error is significant at the 5% level. Panel A of Figure 3 plots the average predicted q against the average realized q from the joint estimation. All the scatter points are largely in line with the 45-degree line, indicating a good fit for the valuation moments.

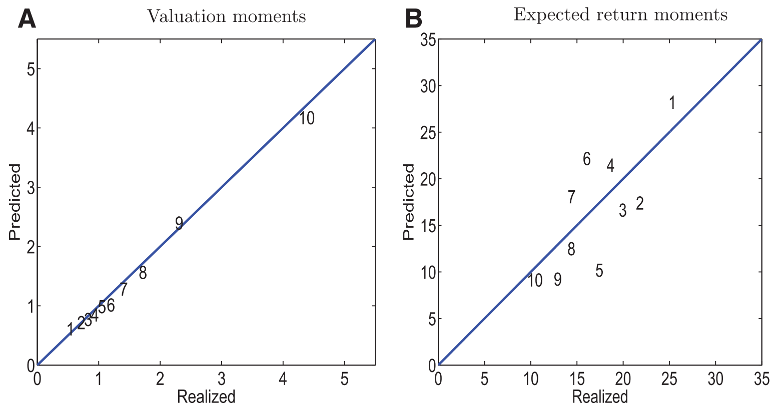

Figure 3
Average predicted *q* versus average realized *q*, average predicted returns versus average realized returns, the Tobin's *q* deciles, joint estimation of the valuation moment and the expected return moment, 1963–2011
The results are one-step GMM on the valuation moment in Equation (10) and the expected return moment in Equation (12) jointly. The Tobin's q deciles are labeled in an ascending order.

Panel B also reports expected return errors across the q deciles. Although occasionally large, the individual errors do not vary systematically with Tobin's q. The high-minus-low decile has a small error of only 3.75% per annum, which is also insignificant. From Panel B of Figure 3, the scatter points of average predicted returns versus average realized returns are aligned with the 45-degree line. In contrast, despite a lower average magnitude, the Carhart alphas move almost monotonically, decreasing from 6.80% to −3.12%, from the low decile to the high decile (Panel B of Table 7). The high-minus-low alpha of −9.92% is more than five standard errors from zero.

3.4 Matching the valuation moment and the investment Euler equation moment jointly

As noted, due to the presence of the market equity, the valuation moment (10) might be subject to the impact of misvaluation. Suppose assets are misvalued, the first-order condition of investment simply forces managers to align investment with asset prices, which might deviate from the present value of future cash flows. To alleviate this concern, we estimate the valuation moment and the investment Euler equation moment (14) jointly. Asset prices do not enter the Euler equation, whose right-hand side is exactly the present value of future cash flows from one additional unit of capital. As such, the Euler equation forces managers to anchor investment on economic fundamentals.

Table 8 reports the results. From Panel A, the slope parameter, η, is estimated to be 4.10, which is close to 4.15 in the benchmark estimation with only the valuation moment (see Table 2). The curvature parameter is estimated to be 4.09, which is again not far from 3.75 reported in Table 2. The capital's share from the Euler equation moment is estimated to be 0.28 ($t=3.07$). The mean absolute

Table 8
GMM estimation and tests for the Tobin's q deciles, joint estimation of the valuation moment and the investment Euler equation moment, 1963–2011

Panel A: Point estimates and the χ^2 tests

η	[t]	ν	[t]	$p_{\nu=2}$	κ	[t]	Φ/Y	$\overline{\vert e_i^q \vert}$	$\overline{\vert e_i^e \vert}$	χ^2	d.f.	p_{χ^2}
4.10	18.88	4.09	18.33	0.00	0.28	3.07	3.95	0.08	0.09	11.80	17	0.81

Panel B: Valuation errors and investment Euler equation errors

	Low	2	3	4	5	6	7	8	9	High	H–L
e_i^q	−0.16	−0.08	−0.03	0.00	−0.03	0.09	0.03	0.06	−0.17	0.11	0.27
[t]	−2.87	−1.65	−0.69	0.09	−0.62	1.86	0.52	1.11	−1.06	1.52	2.58
e_i^e	−0.08	−0.04	−0.05	−0.08	−0.04	−0.10	−0.12	−0.04	0.16	0.24	0.32
[t]	−1.71	−0.98	−1.14	−1.46	−1.10	−1.45	−2.12	−0.94	1.36	1.40	1.53

Panel A reports the one-step GMM results from estimating jointly the valuation moments and the investment Euler equation moments given by Equations (10) and (14), respectively. η is the slope, ν is the curvature of the adjustment costs function, and κ is the capital's share. The t-statistics, denoted [t], test that a given parameter equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$. Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{|e_i^q|}$ is the average magnitude of the valuation errors given by Equation (11). $\overline{|e_i^e|}$ is the average magnitude of the investment Euler equation errors. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that all the errors are jointly zero. Panel B reports for each individual decile and the high-minus-low decile the valuation errors, e_i^q, the investment Euler equation errors, e_i^e, as well as their t-statistics.

valuation error is 0.08, which is close to 0.07 in Table 2. The mean absolute Euler equation error is 0.09. From Panel B, the high-minus-low valuation error is 0.27, which is significant. However, in terms of economic magnitude, the 0.27 estimate is only 6% of the valuation spread across the q deciles. The high-minus-low Euler equation error is slightly larger at 0.32 but insignificant.

Figure 7 plots the predicted q against the realized q as well as the marginal benefits against the marginal costs of investment across the q deciles. Both sets of scatter points are largely aligned with the 45-degree line. As such, the model's performance in fitting the valuation moment alone is robust to the inclusion of the investment Euler equation moment. Overall, the evidence suggests that the impact of misvaluation on our benchmark estimation is relatively small, and that investment is reliably connected with economic fundamentals. The results are consistent with those of Chirinko and Schaller (1996) and Warusawitharana and Whited (2012), who show that misvaluation has little impact on investment policy in the U.S. data.[7]

3.5 Disaggregation and nonlinear marginal costs of investment

In this subsection, we stress-test the model by fitting the valuation moment across the 20, 50, and 100 portfolios formed on q. These portfolios admit substantially larger valuation spreads than the q deciles, thereby raising the power of the tests. We also quantify the importance of the curvature

[7] However, Chirinko and Schaller (2001) report a larger impact of misvaluation on investment in the Japanese data.

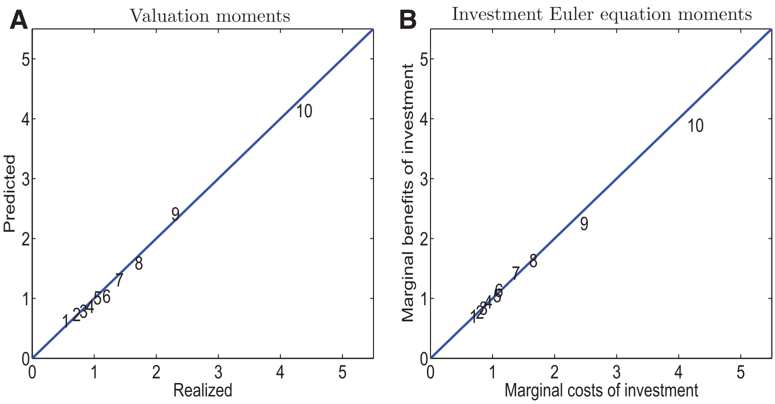

Figure 4
Average predicted q versus average realized q, average marginal costs of investment versus average marginal benefits of investment, the Tobin's q deciles, joint estimation of the valuation moment and the investment Euler equation moment, 1963–2011
The results are one-step GMM on the valuation moment (10) and the (scaled) investment Euler equation moment (14) jointly. The q deciles are labeled in an ascending order. From Equation (14), the marginal costs of investment are $\left(1+(1-\tau_t)\eta^{\nu}\left(\frac{I_{it}}{K_{it}}\right)^{\nu-1}\right)\frac{K_{it+1}}{A_{it}}$, and the marginal benefits $\frac{\left[(1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}}+\frac{\nu-1}{\nu}\left(\eta\frac{I_{it+1}}{K_{it+1}}\right)^{\nu}\right]+\delta_{it+1}\tau_{t+1}+(1-\delta_{it+1})\left[1+(1-\tau_{t+1})\eta^{\nu}\left(\frac{I_{it+1}}{K_{it+1}}\right)^{\nu-1}\right]\right]}{w_{it}r^{Ba}_{it+1}+(1-w_{it})r^{S}_{it+1}}\frac{K_{it+1}}{A_{it}}$.

parameter by estimating the restricted model with $\nu=2$ (quadratic adjustment costs).

3.5.1 The impact of disaggregation. A technical issue arises when we use more disaggregate portfolios in the GMM estimation. As noted in Cochrane (2005, 225): "When the number of moments is more than around 1/10 the number of data points, [the variance-covariance] estimates tend to become unstable and near singular. Used as a weighting matrix, such an [estimated] matrix tells you to pay lots of attention to strange and probably spurious linear combinations of the moments." In our setting, a near singular variance-covariance matrix would imply large standard errors and reduce the power of the χ^2 test.

We have in total 49 annual time series observations from 1963 to 2011, meaning that the optimal number of testing portfolios would be five. The sample length also means that using the 50 and 100 portfolios gives rise automatically to a singular variance-covariance matrix. As such, to maximize the power of the tests, we select portfolios 1, 5, 10, 15, and 20 (labeled in an ascending order) from the q vigintiles, portfolios 1, 13, 25, 37, and 50 from the 50 portfolios, and portfolios 1, 25, 50, 75, and 100 from the 100 portfolios. For comparison, we also report the results from using deciles 1, 3, 5, 7, and 10 from the q deciles. Our selection retains the largest possible q spread across the testing assets,

Table 9
Portfolio-level descriptive statistics for the 10, 20, 50, and 100 portfolios formed on Tobin's q, 1963–2011

Panel A: 10 deciles

	Mean	1	3	5	7	10	10–1	[t]
q_{it}	1.72	0.44	0.77	1.02	1.43	4.94	4.50	12.11
$\frac{I_{it}}{K_{it}}$	0.22	0.15	0.16	0.18	0.22	0.39	0.24	14.70
$\frac{K_{it+1}}{A_{it}}$	0.29	0.30	0.44	0.48	0.49	0.40	0.10	3.44

Panel B: 20 vigintiles

	Mean	1	5	10	15	20	20–1	[t]
q_{it}	2.15	0.35	0.74	1.05	1.68	6.94	6.59	9.82
$\frac{I_{it}}{K_{it}}$	0.25	0.15	0.16	0.18	0.24	0.52	0.37	10.03
$\frac{K_{it+1}}{A_{it}}$	0.41	0.28	0.44	0.49	0.46	0.41	0.13	4.08

Panel C: 50 portfolios

	Mean	1	13	25	37	50	50–1	[t]
q_{it}	2.87	0.25	0.77	1.08	1.70	10.54	10.29	9.86
$\frac{I_{it}}{K_{it}}$	0.29	0.12	0.16	0.19	0.25	0.74	0.61	9.04
$\frac{K_{it+1}}{A_{it}}$	0.40	0.23	0.45	0.45	0.45	0.40	0.17	3.99

Panel D: 100 portfolios

	Mean	1	25	50	75	100	100–1	[t]
q_{it}	3.73	0.20	0.76	1.09	1.77	14.83	14.63	8.69
$\frac{I_{it}}{K_{it}}$	0.32	0.11	0.16	0.19	0.25	0.89	0.78	8.92
$\frac{K_{it+1}}{A_{it}}$	0.40	0.24	0.46	0.45	0.44	0.43	0.19	3.26

This table reports portfolio-level descriptive statistics including the time series averages of Tobin's q, q_{it}; investment-to-capital, I_{it}/K_{it}; and next period capital-to-assets, K_{it+1}/A_{it}, the differences between the high and the lowportfolios, and the t-statistics testing that the differences are on average equal to zero. To avoid near singularity in the estimated variance-covariance matrix, we pick only five testing portfolios out of each set of q portfolios. With an ascending order in labeling portfolios, we use deciles 1, 3, 5, 7, and 10 out of the 10 deciles; vigintiles 1, 5, 10, 15, and 20 out of the 20 vigintiles; portfolios 1, 13, 25, 37, and 50 out of the 50 portfolios; and portfolios 1, 25, 50, 75, and 100 out of the 100 portfolios.

while preventing the resulting variance-covariance matrix from becoming near singular.[8]

Table 9 reports descriptive statistics for the variety of q portfolios. Clearly, more disaggregated portfolios display larger valuation spreads. As noted, the valuation spread across the deciles is 4.50. Using the 20, 50, and 100 portfolios raises the valuation spread to 6.59, 10.29, and 14.63, respectively. The investment-to-capital spread also rises from 0.24 across the deciles to

[8] A similar technique is also often used in consumption-based asset-pricing tests. For instance, Nagel and Singleton (23–24) write: "We choose the small-value, small-growth, large-value, and large-growth portfolios from the six portfolios of Fama and French (1993) as our equity test portfolios. Restricting the set of equity portfolios to these four allows us to keep the number of assets low (small R), but still capture most of the cross-sectional variation in returns related to the 'size' and 'value' effects. Including a larger number of size and book-to-market portfolios would not add much additional return variation, due to the strong commonality in the returns of these portfolios."

Table 10
GMM estimation and tests, the impact of disaggregation, nonquadratic and quadratic adjustment costs, 1963–2011

	Panel A: Nonquadratic adjustment costs				Panel B: Quadratic adjustment costs			
	$N=10$	$N=20$	$N=50$	$N=100$	$N=10$	$N=20$	$N=50$	$N=100$
η	4.10	4.06	3.99	4.00	5.52	6.22	6.96	7.62
$[t]$	18.95	17.11	16.43	18.68	14.07	12.82	10.57	11.49
ν	3.81	3.21	2.96	2.95				
$[t]$	21.64	20.62	21.83	24.69				
$p_{\nu=2}$	0.00	0.00	0.00	0.00				
Φ/Y	4.29	5.68	6.19	6.83	21.74	27.26	32.70	39.26
$\overline{\lvert e_i^q \rvert}$	0.04	0.09	0.11	0.20	1.05	1.31	1.60	2.00
$\overline{\lvert e_i^q \rvert}^{\star}$	0.06	0.20	0.27	0.27	0.88	1.19	1.61	2.14
$\overline{\lvert e_i^q \rvert}/q$	2%	4%	4%	5%	61%	61%	56%	54%
χ^2	4.17	6.74	7.41	7.07	11.12	10.72	9.54	9.18
d.f.	3	3	3	3	4	4	4	4
p_{χ^2}	0.24	0.08	0.06	0.07	0.03	0.03	0.05	0.06
$\triangle e_i^q$	0.08	0.15	0.18	−0.11	2.44	2.64	2.62	3.00
$[t]$	1.76	2.26	2.06	−1.10	3.19	3.03	2.68	2.70
$\triangle e_i^q/\triangle q_i$	2%	2%	2%	−1%	54%	40%	26%	21%

This table reports the estimation results via one-step GMM on the valuation moments given by Equation (10), using 10, 20, 50, and 100 (N) portfolios formed on Tobin's q. To avoid near singularity in the estimated variance-covariance matrix, we pick only five testing portfolios out of each set of q portfolios. With an ascending order in labeling portfolios, $N=10$ means deciles 1, 3, 5, 7, and 10; $N=20$ means vigintiles 1, 5, 10, 15, and 20; $N=50$ means portfolios 1, 13, 25, 37, and 50 from the 50 portfolios; and $N=100$ means portfolios 1, 25, 50, 75, and 100 from the 100 portfolios. η is the slope and ν is the curvature of the adjustment costs function. The t-statistics, denoted $[t]$, test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic that tests $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. In a given column, $\overline{|e_i^q|}$ is the mean absolute valuation error, and $\overline{|e_i^q|}/q$ is the ratio of $\overline{|e_i^q|}$ over the average q across the five selected portfolios. $\overline{|e_i^q|}^{\star}$ is the mean absolute valuation error for all the portfolios in a given column including those not used in the estimation. χ^2, d.f., and p_{χ^2} are the statistic, the degrees of freedom, and the p-value for the χ^2 test on the null that the errors are jointly zero across the five selected portfolios. $\triangle e_i^q$ is the valuation error for the high-minus-low portfolio, and $\triangle e_i^q/\triangle q_i$ is the ratio of $\triangle e_i^q$ over the valuation spread.

0.37, 0.61, and 0.78 across the 20, 50, and 100 portfolios, respectively. The next period capital-to-assets spread increases somewhat from 0.10 across the deciles to, for example, 0.19, across the 100 portfolios.

Panel A of Table 10 reports the GMM estimation and tests on the variety of q portfolios using the benchmark model with nonlinear marginal costs of investment. A comparison between the first column with Table 2 reveals that selecting five deciles out of the original ten increases the power of the χ^2 test. Because of a more precise estimate of the variance-covariance matrix, the p-value of the test drops from 0.47 in Table 2 to 0.24 in Table 10. The power increases even though the point estimates and the valuation errors remain largely unchanged. In particular, the implied adjustment costs-to-sales ratio is 4.29%, which is close to 4.78% in Table 2.

More important, from the remaining three columns in Panel A of Table 10, the benchmark model shows signs of distress once pushed to fit more demanding

q portfolios. Across the 20, 50, and 100 portfolios, the model is rejected by the χ^2 test at the 10% significance level, albeit not at the 5% level. As such, our test has a sufficient amount of power to detect the model's deficiencies.[9]

However, we wish to emphasize that, despite the statistical rejection, the investment model produces only economically small valuation errors, even after we push it to the extreme. Consider the 100 portfolios of q. The mean absolute valuation error is 0.20 across the selective five testing portfolios, which amounts to only 5.36% of the average q across the 100 portfolios. Even when we use the point estimates to value all the 100 portfolios, the mean absolute valuation error is only slightly higher, 0.27, which is 7.24% of the average q. Finally, the valuation error for the high-minus-low portfolio is only -0.11, which in magnitude is about 1% of the valuation spread, 14.63. The valuation errors from matching the 20 and 50 portfolios are also tiny. The model's performance seems remarkable, especially given its simplicity with only two parameters.

3.5.2 The impact of nonlinear marginal costs of investment. Panel A of Table 10 estimates the curvature parameter, ν, to be around three in the benchmark model. The Wald test shows that the estimates are significantly different from two, indicating that the adjustment costs function in the data displays more curvature than the standard quadratic functional form. To quantify the importance of curvature for matching Tobin's q, we estimate the restricted version of the model with ν fixed at two, which implies linear marginal costs of investment.

Panel B reports the detailed results. The quadratic model is formally rejected by the χ^2 test at the 5% significance level with the 10, 20, and 50 portfolios. The model is also rejected at the 10% level with the 100 portfolios but not at the 5% level. In addition, the implied adjustment costs are substantially larger than those from the benchmark model with nonquadratic costs. For instance, the implied adjustment costs-to-sales ratio is 21.74% with the 10 portfolios, which is more than five times 4.29% from the benchmark model and is outside the "plausible" range of 0–20% per Bloom (2009). When we use the 100 portfolios, the implied ratio goes up further, to 39.26%. Clearly, the test has enough power to reject the quadratic model.

Introducing curvature into the adjustment costs function reduces the valuation errors greatly. For instance, with the quadratic costs, the mean absolute error across the five selected deciles is 1.05, which amounts to

[9] Despite a larger valuation spread, the p-value for the χ^2 test with the 100 portfolios (0.07) is not smaller than that with the 50 portfolios (0.06). As such, using more disaggregated portfolios to increase the test's power is not without limitations. Intuitively, as the portfolios become more disaggregated, the average number of firms within each portfolio is reduced. Accordingly, the idiosyncratic standard deviations of the valuation moments are higher, giving rise to larger standard errors. At one point, the larger standard errors start to offset the gain of power from the larger valuation spread across the portfolios, thereby reducing the power of the χ^2 test.

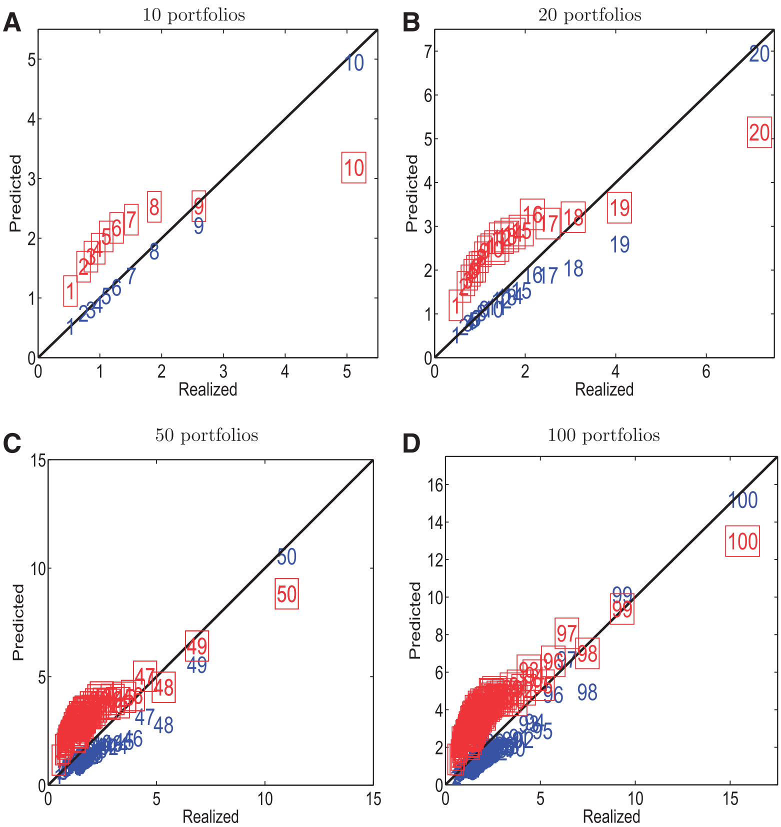

Figure 5
Average predicted *q* versus average realized *q*, 10, 20, 50, and 100 portfolios formed on Tobin's *q*, nonquadratic versus quadratic adjustment costs, 1963–2011
The results are from one-step GMM on the valuation moment in Equation (10). The portfolios are labeled in an ascending order. In each panel, the scatter points in blue are from the model with nonquadratic (nonlinear marginal) adjustment costs, and those boxed in red are with quadratic (linear marginal) adjustment costs.

61% of the average q across the five deciles. The high-minus-low error is 2.44, which is about 54% of the average q for the high-minus-low decile (Panel B of Table 10). In contrast, adding the curvature parameter reduces the mean absolute error to a tiny 0.04 (about 2% of the average q across the portfolios) and the high-minus-low error to 0.08 (about 2% of the valuation spread).

Panel A of Figure 5 confirms that the quadratic model fails to match the valuation spread across the q deciles. The scatter points deviate substantially from the 45-degree line, especially for the high decile. In contrast, the benchmark model with nonquadratic costs does a good job. The scatter points from that model are largely aligned with the 45-degree line. The remaining panels in the figure show a largely similar pattern, although the individual errors appear smaller as a percentage of the valuation spreads (because of their larger magnitude).

Why does the curvature parameter help the model match Tobin's q? Intuitively, with quadratic adjustment costs, investment-to-capital is proportional to Tobin's q because the marginal costs of investment are linear in investment. With curvature, q is a nonlinear (convex) function of investment, as shown in Equation (5). For a given magnitude of spread in investment-to-capital, the convexity magnifies the investment-to-capital spread to produce a larger spread in Tobin's q.[10]

3.6 Industry-specific estimation

We also use the investment model to match the valuation spread within a given industry. Because the valuation spread varies across industries, this test provides an additional set of moments for the model to match. The industry-specific test also allows technological heterogeneity across industries.

To ensure a sufficient number of firms in each portfolio, we strike a balance between the number of industries (the degree of industry heterogeneity) and the number of the q portfolios within each industry. As noted, the length of our time series observations (49 years) implies the use of five testing portfolios within each industry. Given this choice, we use as many industries as possible.

This strategy leads us to the 30-industry classifications per Fama and French (1997), except for utilities, financials, beer, smoke, and coal industries. We exclude utilities and financials because, as noted, the neoclassical theory of investment does not apply to regulated or financial firms (these firms are also excluded from the main tests). In addition, we exclude the beer, smoke, and coal industries because of their insufficient number of firms to form five q portfolios. The beer, smoke, and coal industries have on average 9.59, 7.50, and 7.05 firms per year from 1963 to 2011. As such, each quintile would have fewer than two firms on average per year. Within each industry included, we sort all stocks into five quintiles based on Tobin's q at the end of June of each year t. We hold the portfolios from July of year t to June of year $t+1$, and the portfolios are rebalanced in June.

Panel A of Table 11 reports the descriptive statistics and the GMM estimation within each industry. Tobin's q ranges from 0.83 for Txtls (textiles) to 2.80 for Hlth (healthcare, medical equipment, and pharmaceutical products). The cross-industry average of q is 1.38, and the standard deviation is 0.42. The valuation spread across the extreme q quintile varies from 0.81 for Txtls to 5.36 for Hlth. The cross-industry average of the valuation spread is 2.31, and the standard deviation is 1.08. However, the investment-to-capital spread varies

[10] Prior studies have shown that the nonlinearity in the marginal costs of investment is important for understanding quantity data and stock market data (e.g., Barnett and Sakellaris 1998; Israelsen 2010; Jermann 2010; Bustamante 2012; Gala and Gomes 2013). We add to this body of evidence using data on cross-sectional asset prices.

Table 11
Industry-level descriptive statistics, industry-specific GMM estimation and tests, 1963–2011

	Panel A: Descriptive statistics							Panel B: GMM estimation and tests									
	Firms	q_{it}	$\frac{I_{it}}{K_{it}}$	$\frac{K_{it+1}}{A_{it}}$	$\triangle q_{it}$	$\triangle \frac{I_{it}}{K_{it}}$	$\triangle \frac{K_{it+1}}{A_{it}}$	η	$[t]$	ν	$[t]$	$p_{\nu=2}$	Φ/Y	$\overline{\lvert e_i^q \rvert}$	p_{χ^2}	$\triangle e_i^q$	$[t]$
Food	65	1.48	0.18	0.39	2.54	0.09	0.11	4.87	23.51	4.37	6.95	0.00	3.08	0.18	0.05	0.16	1.60
Games	65	1.29	0.26	0.41	2.03	0.16	0.24	3.46	16.24	2.48	5.78	0.26	12.23	0.12	0.12	0.22	1.73
Books	45	1.35	0.18	0.30	2.01	0.09	0.06	4.70	7.87	4.64	3.17	0.07	4.73	0.16	0.19	0.02	0.09
Hshld	65	1.55	0.22	0.29	2.95	0.10	0.14	4.21	11.16	5.30	5.04	0.00	8.50	0.09	0.68	0.02	0.14
Clths	47	1.17	0.23	0.20	1.84	0.22	0.03	5.39	21.70	2.53	13.49	0.00	7.53	0.11	0.11	0.27	2.02
Hlth	220	2.80	0.24	0.34	5.36	0.23	−0.01	5.84	20.39	2.67	9.79	0.01	19.42	0.42	0.02	0.44	2.62
Chems	66	1.31	0.19	0.46	1.84	0.11	0.06	3.94	11.56	5.42	3.77	0.02	3.61	0.16	0.60	0.07	0.54
Txtls	39	0.83	0.19	0.38	0.81	0.09	0.03	3.65	21.52	3.47	7.44	0.00	2.34	0.04	0.14	0.09	2.33
Cnstr	125	1.06	0.16	0.38	1.62	0.10	0.12	4.59	17.86	4.07	9.96	0.00	2.66	0.05	0.26	0.06	1.58
Steel	57	0.93	0.15	0.49	1.22	0.10	−0.05	4.16	30.47	4.72	9.03	0.00	1.04	0.10	0.01	0.16	2.92
FabPr	133	1.22	0.20	0.28	1.83	0.14	0.05	4.72	19.00	3.32	9.20	0.00	6.48	0.04	0.18	0.09	1.79
ElcEq	48	1.49	0.22	0.27	2.58	0.11	0.08	4.56	9.44	3.72	5.24	0.02	6.99	0.13	0.04	0.21	1.60
Autos	54	1.02	0.24	0.33	1.44	0.07	−0.01	3.33	12.62	5.29	4.40	0.01	3.08	0.24	0.01	0.41	3.12
Carry	29	1.00	0.22	0.29	1.24	0.08	0.10	3.93	11.16	3.49	4.32	0.07	3.18	0.05	0.24	0.14	1.91
Mines	31	1.92	0.32	0.60	3.72	0.53	0.07	3.03	19.59	2.40	8.95	0.13	13.12	0.22	0.29	0.34	1.70
Oil	132	1.40	0.23	0.73	1.89	0.19	0.18	2.58	12.70	2.94	10.92	0.00	2.49	0.06	0.04	0.10	2.76
Telcm	83	1.42	0.24	0.54	2.21	0.21	−0.05	3.12	12.77	2.87	5.44	0.10	8.75	0.09	0.08	0.12	2.34
Servs	271	2.07	0.35	0.30	4.82	0.36	0.08	2.91	4.96	4.11	4.77	0.01	4.46	0.16	0.16	−0.14	−2.07
BusEq	286	1.86	0.32	0.33	3.73	0.31	0.10	3.71	13.49	3.20	12.69	0.00	14.90	0.05	0.82	−0.02	−0.28
Paper	61	1.17	0.16	0.54	1.67	0.08	0.04	4.15	17.48	8.44	3.58	0.01	0.80	0.06	0.66	0.01	0.12
Trans	78	1.04	0.17	0.72	1.46	0.20	0.02	2.88	12.13	5.17	4.54	0.01	0.18	0.07	0.04	0.15	2.91
Whlsl	94	1.15	0.23	0.22	1.96	0.17	0.09	4.80	12.50	2.35	10.78	0.11	5.55	0.09	0.05	0.08	1.48
Rtail	84	1.26	0.22	0.37	2.27	0.17	0.20	3.97	19.39	3.60	13.03	0.00	1.71	0.06	0.05	−0.06	−0.90
Meals	59	1.46	0.17	0.68	2.38	0.21	0.29	3.31	13.87	2.53	8.32	0.08	6.36	0.09	0.13	0.17	1.97
Other	141	1.28	0.21	0.39	2.31	0.22	0.26	3.65	14.25	2.63	8.52	0.04	5.38	0.10	0.25	0.08	1.23
Mean	95	1.38	0.22	0.41	2.31	0.17	0.09	3.98		3.83			5.94	0.12		0.15	

This table reports industry-specific estimation for each of the 30-industry classifications per Fama and French (1997), except for utilities, financials, beer, smoke, and coal. Within each industry, we sort all stocks into five quintiles on Tobin's q at the end of each June. Within each industry, Panel A reports the averages of the number of firms; Tobin's q, q_{it}; investment-to-capital, $\frac{I_{it}}{K_{it}}$; next period capital-to-assets, $\frac{K_{it+1}}{A_{it}}$; as well as the valuation spread, $\triangle q_{it}$; the investment-to-capital spread, $\triangle \frac{I_{it}}{K_{it}}$; and the next period capital-to-assets spread, $\triangle \frac{K_{it+1}}{A_{it}}$. Panel B reports industry-specific GMM estimation and tests. η is the slope and ν is the curvature of the adjustment costs function. The t-statistics, denoted $[t]$, test that a given point estimate equals zero. $p_{\nu=2}$ is the p-value associated with the Wald statistic testing $\nu=2$ (quadratic adjustment costs). Φ/Y is the ratio in percent of the implied capital adjustment costs over sales. $\overline{\lvert e_i^q \rvert}$ is the mean absolute valuation error. p_{χ^2} is the p-value for the χ^2 test on the null that all the valuation errors are jointly zero. The last two columns report the valuation errors for the high-minus-low quintiles and their t-statistics.

from 0.08 for Paper (business supplies and shipping containers) to 0.53 for Mines (precious metals, nonmetallic, and industrial metal mining).

Panel B reports the GMM results from fitting the valuation moments of the q quintiles within each industry. The parameter estimates vary across industries and seem economically sensible. The slope parameter, η, is significantly positive across all the industries. The estimate varies from 2.58 for Oil (petroleum and natural gas) to 5.84 for Hlth with a cross-industry average of 3.98. For the curvature parameter, ν, its magnitude varies from 2.35 for Whlsl (wholesale) to 8.44 for Paper with a cross-industry average of 3.83. The Wald test fails to reject the quadratic costs specification for only 7 out of 25 industries and rejects the null for the remaining 18 industries.

The implied adjustment costs as a percentage of sales is on average 5.94% across the industries. To calculate this ratio for a given industry, we aggregate all the investment, capital, and sales across all the firms within the industry, compute the adjustment costs series by plugging these industry-level aggregates into Equation (2), and then taking the time series average of the adjustment costs-to-sales ratio. We observe that the ratio varies greatly across the industries, including low estimates such as 0.18% for Trans (transportation) and 0.8% for Paper as well as the high estimates such as 14.9% for BusEq (business equipment) and 19.42% for Hlth. In total, 4 out of 25 industries have adjustment costs above 10% of sales (albeit below 20%), indicating that the benchmark model might be misspecified for these industries.

Panel B shows that the mean absolute valuation errors seem small across the industries. The cross-industry average is 0.12, which amounts to 8.7% of the cross-industry average q. The mean absolute valuation errors vary from 0.04 for Txtls and FabPr (fabricated products and machinery) to 0.42 for Hlth. In terms of a percentage of industry-specific average q, the mean errors vary from 2.69% for BusEq (business equipment) to 23.53% for Autos (automobiles and trucks). The χ^2 test formally rejects the benchmark model for 7 out of 25 industries at the 5% significance level. Given the model's parsimony with only one capital input, the rejection across some industries is not surprising. Other inputs such as intangible capital or quasi-fixed labor are omitted, but can contribute to Tobin's q. What is perhaps more surprising, to us at least, is the small q errors for many industries achieved in the parsimonious model.

The last two columns of Table 11 report the errors for the high-minus-low q quintiles, $\triangle e_i^q$, and their t-statistics for all the industries. The high-minus-low errors vary in magnitude from 0.01 for Paper to 0.44 for Hlth. The cross-industry average is 0.15, which represents 6.49% of the valuation spread averaged across the industries. As a percentage of industry-specific valuation spread, the high-minus-low errors vary in magnitude from 0.54% for BusEq to 28.47% for Autos. Ten out of 25 industries have significant high-minus-low errors at the 5% level. Figure 6 illustrates the good fit of the benchmark model in matching

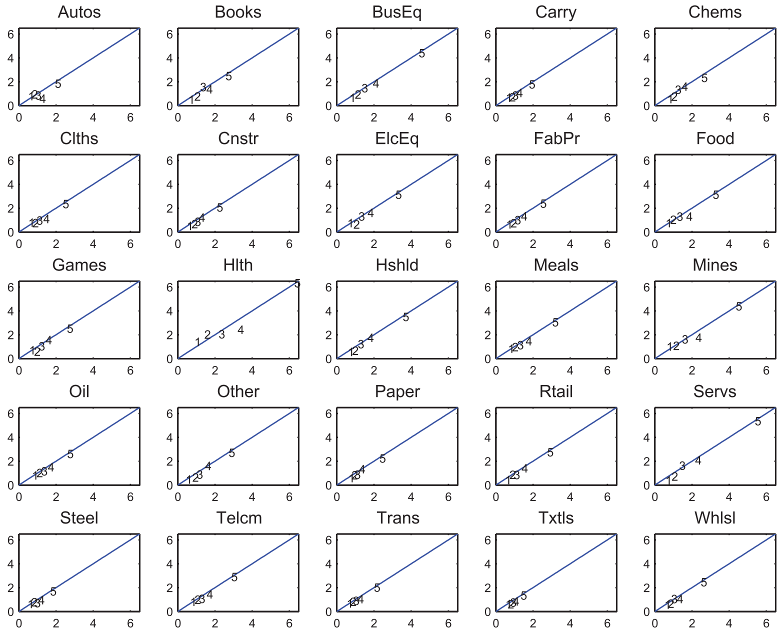

Figure 6
Average predicted versus average realized Tobin's q, industry-specific estimation, 1963–2011
This figure reports industry-specific estimation for each of the 30-industry classifications per Fama and French (1997), except for utilities, financials, beer, smoke, and coal. The remaining 25 industries are: Automobiles and trucks (Autos), Printing and publishing (Books), Business equipment (BusEq), Aircraft, ships, and railroad equipment (Carry), Chemicals (Chems), Apparel (Clths), Construction and construction materials (Cnstr), Electrical equipment (ElcEq), Fabricated products and machinery (FabPr), Food products (Food), Recreation (Games), Healthcare, medical equipment, pharmaceutical products (Hlth), Consumer goods (Hshld), Restaurants, hotels, motels (Meals), Precious metals, nonmetallic, and industrial metal mining (Mines), Petroleum and natural gas (Oil), Everything else (Other), Business supplies and shipping containers (Paper), Retail (Rtail), Personal and business services (Servs), Steel works (Steel), Communication (Telcm), Transportation (Trans), Textiles (Txtls), and Wholesale (Whlsl). The testing portfolios are five Tobin's q quintiles within each industry. The results are from estimating the investment model via one-step GMM in each industry with the valuation moment in Equation (10). The quintiles are labeled in an ascending order. In each panel, the y-axis is the average predicted q, and the x-axis is the average realized q.

the valuation moments with each industry. We plot the average predicted q against the average realized q for the Tobin's q quintiles within each industry. All the scatter points are largely aligned with the 45-degree line.

Taken together, the industry-specific estimation provides robust evidence on technological heterogeneity across industries. Although the benchmark model seems misspecified for some industries, the overall evidence suggests that the investment model is a good start to understanding valuation.

4. Conclusion

We develop a new methodology for equity valuation based on the q-theory of investment. The basic idea is that managers, if behaving optimally, will adjust the supply of capital assets via real investment to the changes in the market value of the assets. As such, one can value the assets via managers' investment costs of supplying the assets. Through extensive empirical tests, we show that the supply approach seems a good start to understanding the cross-section of asset prices.

While the supply approach and the traditional present value approach are complementary in nature, we argue that the supply approach has important advantages in practice. With the observable investment-to-capital in the current period as the only input, the supply approach is straightforward to implement. In contrast, the present value approach requires cash flow forecasts and discount rate estimates many years into the future. Both inputs come with large standard errors, which render the resulting valuation estimates imprecise and likely even biased.

It should be noted that the supply approach does not relieve the burden of managers to forecast the cash flows of their own investment projects and the appropriate discount rates. As such, the supply approach is more applicable to outside investors who are interested in estimating the intrinsic value of a firm. In addition, to the extent that managers have better inside information about their own projects than outsider investors (e.g., Myers and Majluf 1984), the supply approach can be informative about the "right" market value. As such, the supply approach can be applied to evaluate the "fairness" of the market price in mergers and acquisitions as well as equity issues and repurchases. As a cross-check to the traditional present value calculations, the supply approach can also be used to evaluate the performance of equity analysts. Finally, the supply approach is particularly useful for valuing plants, private firms, and initial public offerings. Because stock returns data are not available for these entities, the discount rates cannot be estimated. As such, the supply approach would be a more viable approach in these applications.

We view our work only as a first stab at integrating asset pricing with the equity valuation (and fundamental analysis) literature in corporate finance and accounting. The quantitative results from the first stab seem encouraging. Ultimately, valuation should be done at the firm level. One can develop new econometric methodologies to take the structural valuation equation to the firm-level data. The valuation framework can be extended to incorporate additional productive inputs such as labor and intangible assets. Nonconvex adjustment costs can be modeled as in Abel and Eberly (1994) and alternative investment adjustment costs as in Eberly, Rebelo, and Vincent (2012). Corporate finance frictions such as financial constraints, nonseparability between investment and financing decisions (e.g., Hennessy and Whited 2007) and agency conflicts between shareholders and managers (e.g., Albuquerque and Wang 2008) can be incorporated and their valuation impact quantified. More generally, a deep unification between asset pricing and the accounting valuation (e.g., Koller, Goedhart, and Wessles 2010) should be pursued.

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