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Firm Size and Corporate Investment

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corporate investment, size effects

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Firm Size and Corporate Investment*

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ABSTRACT

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1 Introduction

We investigate the dynamics of firm growth in the United States. The focus is on the relationship between firm size and investment rates. The gross investment rate of publicly traded firms in the bottom decile of the size distribution averages about 33.3 percent per annum, and is about two times that of firms in the top size decile. This inverse capital growth-size relationship has been previously documented under different forms in the empirical industrial organization literature.[1] However, little is known about whether the dependence on size holds conditionally, that is even after controlling for variables known to affect a firm's optimal investment policy. While much progress has been made in understanding the role of Tobin's Q and cash flow in investment regressions, several fundamental questions still remain unanswered. Why do small firms invest significantly more than large ones? What is the role of firm size and how quantitatively important is it in explaining the dynamics of corporate investment? Is firm size relevant because the economy is finite and diminishing technological returns and/or potentially increasing cost of capital (due to capital market imperfections) set in eventually? These questions are central to understanding the investment dynamics at the firm level and have important implications for aggregate investment and economic growth.

Modern theories of firm investment identify in Tobin's Q and cash flow measures the main observable determinants of optimal corporate investments as they summarize relevant information about a firm's expected future profitability and financing conditions. Accordingly, we investigate whether there is any role for firm size even after accounting for standard empirical proxies of heterogeneity in firms' technological investment opportunities and financial status. We provide evidence of a size effect in corporate investment rates: a firm's investment rate is inversely related to its size (as measured by its capital stock) even after controlling for factors known to affect a firm's optimal investment policy such as Tobin's Q and cash flow, among others.

The size effect in corporate investment is both economically and statistically meaningful. The economic relevance of variation in firm size is at least twice as important as that in Tobin's Q and cash flow.

[1]Among others, Evans (1987) and Hall (1987) provide evidence that the growth rate of manufacturing firms is negatively associated with firm size and firm age. Using different datasets with only a limited time span available, they measure firm size using mainly employment data.

Statistically, firm size accounts for a sizable fraction of the total variation in corporate investment and its contribution is of the same order of magnitude as Tobin's Q and cash flow. The size effect is robust to the choice of empirical proxies of investment opportunities and financial status, timing of variables, sample selection, nonlinear specifications, alternative samples, lagged investment effects (Eberly, Rebelo and Vincent, 2011), and classical measurement errors. Given the evidence in Erickson and Whited (2000), the robustness of the size effect to measurement error in Tobin's Q is of particular concern. Using instrumental variable estimation, alternative measures of Tobin's Q as in Cummins, Hassett and Oliner (2006), and the methodology in Erickson and Whited (2005), we find no evidence that the size effect is driven by classical measurement error in Tobin's Q. Most importantly, the relationship between firm size and investment is more robust to possible measurement errors in the proxies for Tobin's Q than is the relationship between investment and cash flows. Therefore, firm size not only contributes to explaining first-order variation in investment, but also, and unlike cash flow, its contribution is more robust to measurement error in Tobin's Q.

These strong size-investment relationship findings motivate the natural question of why size matters. For instance, Tobin's Q and cash flow may not be sufficient statistics for investment opportunities and financial status, but rather may be only imperfect observable proxies. According to the neoclassical theory of investment (Hayashi, 1982; Abel and Eberly, 1994), homogeneity of equal degree of a firm's operating profit and investment cost functions makes Tobin's Q proportional to marginal q, and hence a sufficient statistic for investment. However, departures from homogeneity due to technological frictions (Gomes, 2001; Cooper and Ejarque, 2003; Alti, 2003; Cooper and Haltinwanger, 2006; Gala, 2012; Abel and Eberly, 2010) and/or the existence of financial frictions (Hennessy, 2004; Hennessy and Whited, 2007; Hennessy, Levy and Whited, 2007; Bolton, Chen, and Wang, 2012), may drive a wedge between the observable Tobin's Q and the unobservable marginal q, thus leading to an omitted variables problem in standard empirical specifications of investment. In this context, the inclusion of firm size may improve the measurement of the true unobservable future investment opportunities and financing conditions. Specifically, our findings suggest that size may be capturing some aspects of a firm's technological decreasing returns to scale and/or increasing returns to scale in the cost of external financing not captured by Tobin's Q and cash flow.

We investigate whether firm size captures mismeasurement of real investment opportunities and/or financial status. If a firm's size captures mismeasurement of a firm's financial status, then we would expect the size effect for financially constrained firms to differ from those for financially unconstrained firms, ceteris paribus. We identify financially constrained firms using the three most prominent empirical measures of a firm financial status, namely the Kaplan-Zingales (1997), the Whited-Wu (2006), and the Hadlock-Pierce (2010) indexes. We find no evidence of significant differences in the estimates between financially constrained and unconstrained firms, suggesting that the findings do not arise because of mismeasurement in financial status.

We further investigate whether a firm's size captures mismeasurement of a firm's true unobservable technological investment opportunity set. In this case, the findings would require larger firms to have lower investment rates because firms' profits exhibit decreasing returns to scale in capital, ceteris paribus. If this was the case, we would expect the (negative) coefficient on firm size to depend positively on the degree of technological returns to scale in firms' profits. We document the existence of such a relationship across industries. Hence, the empirical evidence suggests that the size effect captures some aspects of a firm's technological investment opportunity set that is not captured by Tobin's Q and cash flow.

Overall, the empirical evidence suggests that firm size captures technological decreasing returns to scale rather than differences in financial status. Consistent with such evidence, we focus on a simple Q-theory model of investment with no financial frictions to replicate quantitatively the empirical findings of a size effect. Using simulated method of moments (SMM), we estimate a simple neoclassical model of investment with curvature in the profit function and convex cost of capital adjustment. We then show in simulated data how technological decreasing returns to scale, and measurement error in Tobin's Q, can generate quantitatively the empirical relationship between size and investment results. The model replicates successfully not only the magnitude of the estimates, but also the corresponding variance decomposition of investment in actual data.

The presence of curvature in the profit function, reflecting, for example, market power or decreasing returns to scale in production, allows to replicate the size effect via mismeasurement of marginal q. The significance of firm size would therefore reflect the fact that in a world of many state variables a single variable like Tobin's Q may not capture all available information. In fact, the inclusion of firm size in a simple investment equation would improve the measurement of the underlying variation in marginal q, and hence in investment. With only two state variables in the model, and consistent with the findings in Erickson and Whited (2000), we include measurement error in Tobin's Q to generate cash flow effects in investment regressions, and thus the size effect on *both* Tobin's Q and cash flow.

Our findings have several implications. First, the empirical evidence shows that firm size is at least as important as Tobin's Q and cash flow, both economically *and* statistically, in explaining variation in corporate investments. Unlike cash flow, however, the contribution of firm size to explain first-order variation in investment is more robust to measurement error in Tobin's Q.

Second, we provide empirical evidence on the role of firm size in explaining observed corporate investment policies. In the existing literature, firm size, if ever used, is employed at times either as a catch-all variable to mitigate omitted variable bias or as sorting variable for identification of financially constrained firms prior to estimation of investment equations. Our empirical analysis provides an explicit role for firm size as proxy for unobservable real investment opportunities in the estimation of investment equations. The evidence suggests that standard homogeneity assumptions in modeling a firm's profit function are indeed violated in firm-level data, and hence the dependence of investment on the unobservable marginal q can be better measured empirically by accounting for the observable Tobin's Q/cash flow *and* firm size.

Third, we show that a neoclassical model of investment with curvature in the profit function and quadratic capital adjustment costs can generate *quantitatively* an important size effect. Our aim is obviously not to provide a new model of investment, but rather to show how, even a simple model with no financial frictions, which realistically departs from the traditional homogeneity assumptions, implies the use of firm size to explain first-order variation in investment. Such implication is present in many recent models of investment with curvature. However, except for Gala and Gomes (2016), most of the attention in the literature has been devoted mainly on understanding cash flow effects and other financial variables, while largely ignoring the fact that firm size itself as state variable is a first-order determinant of investment. Our contribution then naturally complement the findings of such models.

The remainder of this paper proceeds as follows. Section 2 describes the data employed in the empirical analysis and presents our main empirical results on the relationship between firm size and investment rates. Section 4 investigates the role of firm size as proxy for real investment opportunities and/or financial status. Section 4 explains the model and presents the estimation results including evidence on our model's ability to explain the size effect. Section 5 concludes. The appendix provides details about the robustness tests on the empirical analysis, estimation of technological returns to scale, and SMM estimation of the model.

2 Empirical Results

In this section we first describe the data used in the empirical analysis, and then we conduct formal tests for the presence of a size effect in investment.

2.1 Data

Our main sample of firms is a balanced panel of US firms from Compustat with annual data for the period 1980-2006. The sample includes 340 firms with 9,180 firm-year observations. We use data for the four main variables present in this study: investment (I/K), Tobin's Q (Q), cash flow (CF), and firm size (K). Investment is defined as capital expenditures in property, plant and equipment scaled by the beginning-of-year capital stock. The capital stock is defined as net property, plant and equipment. Tobin's Q is computed as the market value of assets (defined as the book value of assets plus the market value of common stock minus the book value of common stock) scaled by the book value of assets[2]. Cash flow is calculated as the sum of end-of-year earnings and depreciation scaled by the beginning-of-year capital stock. Firm size is the natural logarithm of the beginning-of-year capital stock. We describe the data and sample selection in more detail in Appendix A.

[2]Erickson and Whited (2006) show that using a perpetual inventory algorithm to estimate the replacement cost of capital and/or a recursive algorithm to estimate the market value of debt barely improves the measurement quality of the various proxies for Q.

We focus on a balanced panel to mitigate potential concerns related to the entry and exit of firms in the database and because the time dimension of the data helps identifying the dynamics of the model. We also investigate the robustness of our size effect results in (i) a large unbalanced panel of US firms from Compustat for the period 1962-2006; and (ii) a panel of international firms from Thomson Financial's Worldscope for the period 1980-2005. We report summary statistics for the main variables of interest and the results for the size effect tests based on these additional samples in Appendix A.

2.2 The Role of Size in Firm Investments

We begin our examination of the relationship between firm size and investment by sorting all firms into separate size decile portfolios. We calculate the size decile breakpoints and rebalance the portfolios each year. We then compute an equal-weighted average of firm investment rates for each size decile. Table 1 reports the mean investment rate and its corresponding robust standard errors for each size decile. The mean investment rate declines from the smallest size decile to the largest decile. The annual investment rate of firms in the bottom decile of the size distribution averages about 33.3 percent, and is about two times that of firms in the top size decile. The strong negative relationship between size deciles and investment rates provides a clear preliminary evidence of a size effect among the firms in our sample.[3]

We now turn to formally test whether the importance of size holds conditionally in a regression framework. Table 2 reports the estimation results for various specifications of the investment regression in (**??**). We use the beginning-of-year capital stock as a measure of firm size[4]. We begin by testing an unconditional size effect among our sample of firms by estimating a univariate regression of investment rates on firm size. The results in specification (1) show clearly that smaller firms grow faster than large firms. The coefficient estimate is about -0.02 and statistically significant. This magnitude is quite large in economic terms, as a one standard deviation increase in the log size of a firm leads to an average decrease in its

[3]The size/investment relationship is even stronger in the unbalanced panel of US firms for the period 1962-2006. The gross investment rate for firms in the smallest size decile (45.3%) is about 2.3 times that of firms in the largest size decile (19.8%). Results available upon request.

[4]We obtain similar results when using past lags of capital stock either in place of or as instrument for beginning-of-year capital stock. Given that we also scale end-of-year investment by beginning-of-year capital, this rules out any possibility that our findings are mechanically driven. Results reported in Appendix A.

investment rate of about 4.3 percent per annum. Our results clearly reject the proposition of Gibrat (1939) that growth rates and size are independent.

The negative relationship between firm size and investment in the empirical tests may be driven by heterogeneity in firms' investment opportunities and/or financial status. For instance, small firms tend to have higher values of Tobin's Q compared to large firms, and will therefore tend to have also higher investment rates according to the Q-theory of investment. We now test for the presence of a conditional size effect, or the proposition that small firms grow faster than large firms even after controlling for proxies of investment opportunities and financial status. The simplest approach to control for heterogeneity in the determinants of firm investments is to include firm and time dummies to the baseline regression. As shown in the second column of Table 2, the negative relationship between firm size and investment remains unaffected even after controlling for general unobserved heterogeneity. With fixed effects, a one-standard deviation increase in firm size above its average value leads to a 15.4 percent investment reduction relative to its average investment rate.

According to the Q-theory of investment (Hayashi, 1982), all heterogeneity in the determinants of firm investments can be conveniently summarized in a single variable, namely Tobin's Q. Hence, we include Tobin's Q in the set of control variables proxying for the determinants of firm investment. Specification (3) in Table 2 shows that the coefficient on firm size is still negative and statistically significant, even after controlling for variation in Tobin's Q. The inclusion of Tobin's Q, while increasing the adjusted R^2 from 27 to 32 percent, has overall only a marginal impact on the size effect estimate. With fixed effects and Tobin's Q, a one-standard deviation increase in firm size above its average value leads to an average decrease in investment rates by 14.5 percent relative to its average investment rate. For comparison, a one standard deviation increase in Tobin's Q above its average value leads to an average increase of about 5.1 percent in a firm's investment rate relative to its average value.

Traditional investment-Q regressions are often augmented with cash flow variables to describe firm investments. Cash flow is generally used either as proxy for a firm's financial status (Fazzari, Hubbard, and Petersen, 1988; Hubbard, 1998) or interpreted as the byproduct of mismeasurement in marginal q (Erickson and Whited, 2000; Gomes, 2001; Cooper and Ejarque,2003; Gala and Gomes, 2012). In addition, Erickson and Whited (2000, 2006 and 2012) make also a compelling case for substantial measurement error in Tobin's Q. Hence, we include also cash flow in our set of control variables proxing for a firm's investment opportunities and/or financial status. Specification (4) in Table 2 confirms the presence of size effects. The inclusion of cash flow affects only marginally our results, with the adjusted R^2 increasing only up to 35 percent and the size estimate being virtually unaffected. The empirical results also confirm the economic importance of firm size relative to Tobin's Q and cash flow. A one standard deviation increase in a firm size above its average value leads to a 10.9 percent investment reduction relative to its average investment rate. For comparison, a one standard deviation increase in Tobin's Q above its average value leads to a 3.8 percent investment increase relative to its average investment rate. Similarly, a one standard deviation increase in cash flow above its average value leads to a 4.7 percent investment increase relative to its average investment rate.

The results reported in Table 2 provide strong evidence of size effects in corporate investment among publicly traded firms: small firms grow faster than large firms, even after controlling for differences in Tobin's Q and cash flow. Our estimates show that firm size is at least twice as economically important as Tobin's Q and cash flow in explaining differences in investment rates.

We confirm our results in a large battery of robustness tests. Among others, we investigate the robustness of the size effect to measurement error in Tobin's Q, sample selection, omitted variables, timing of variables, nonlinear specifications, and alternative samples. In the interest of clarity and ease of exposition, we discuss and report these additional tests in Appendix A.

2.3 Variance Decomposition of Firm Investments

We now examine the relative importance of the determinants of investment rates by performing an analysis of covariance based on various specifications of the investment regression in (**??**). Table 3 reports the results of this covariance decomposition for several specifications. Following Lemmon, Roberts and Zender (2008), we calculate the Type III partial sum of squares for each effect and scale it by the total sum of squares for each specification.[5] The normalization by total Type III partial sum of squares forces the

[5] We use Type III sum of squares because the sum of squares is not sensitive to the ordering of the covariates.

column values to sum to one and each number reported is interpreted as the fraction of the model sum of squares attributed to that particular effect (i.e. firm, year, Tobin's Q, etc.). We also report the adjusted R^2 for each specification.

The first column of Table 3 reports the results with only firm and year fixed effects. The adjusted R^2 indicates that firm and year fixed effects account for 22 percent of the variation in investment rates, of which about 80 percent can be attributable to firm fixed effects alone. This confirms the importance of including firm fixed effects to control for unobserved long-run or steady-state heterogeneity in the determinants of firm investments. Year fixed effects, which capture unobserved aggregate variation, account instead for, at most, only 20 percent of the total explained variation in investment.

The addition of firm size increases the adjusted R^2 to 27 percent, with 17 percent of the total explained variation in investment attributable to firm size alone. The inclusion of Tobin's Q as a control for observed time-varying heterogeneity in the determinants of firm investments brings the adjusted R^2 up to 32 percent. Importantly, firm size still contributes to about 14 percent of the total explained variation in investment, which is about as much as Tobin's Q. The full specification including also cash flow as a control for heterogeneity in a firm's investment opportunities and/or financial status has an adjusted R^2 of 35 percent. Most importantly, the fraction of the explained sum of squares attributable to firm size (9 percent) is of the same order of magnitude as Tobin's Q (10 percent) and cash flow (13 percent).

Overall, the variance decomposition in Table 3 highlights the quantitative importance of size. Firm size is at least as important as Tobin's Q and cash flow, both economically *and* statistically, in explaining variation in corporate investments.

3 Financial Frictions or Real Investment Opportunities?

The economic and statistical of a size effect in corporate investment motivates the question of why firm size matters. For instance, Tobin's Q and cash flow may not be sufficient statistics for investment opportunities and financial status, but rather may be only imperfect observable proxies. It is well known that under the standard Hayashi (1982) conditions of linear homogeneity in a firm's profit function, average Tobin's Q is identical to marginal q and hence a sufficient statistic for firm investment decisions. However, various violations of these conditions due to technological and/or external financing frictions, including market power, decreasing returns to scale in production, inhomogeneous costs of investment and/or external financing, may drive a wedge between the "observable" Tobin's Q and the unobservable marginal q, thus leading to an omitted variables problem in standard empirical specifications of investment. In this context, the inclusion of firm size may improve the measurement of the true unobservable future investment opportunities and financing conditions. Specifically, our findings suggest that firm size may be capturing some aspects of technological decreasing returns to scale in a firm's profit function and/or increasing returns to scale in the cost of external financing not captured by Tobin's Q and cash flow. In other words, the larger the firm size, the lower the return on investment and/or the more costly the external financing, and the lower the firm growth, ceteris paribus.

In this section, we investigate whether firm size captures mismeasurement of technological investment opportunities and/or financial status - i.e. a firm's degree of external financing constraints.

3.1 Firm Size and Financial Frictions

We first examine whether our size effect estimates are simply reflecting the degree of external financing constraints that a firm may be facing. If firm size truly reflects the degree of external financing constraints, then the empirical findings would require larger firms to be more constrained compared to smaller firms, and thus experience more costly external financing and lower investment. However, this interpretation would be at odds, for instance, with the empirical evidence in Hennessy and Whited (2007), and more generally the large literature on cash flow sensitivities of investment, which often uses firm size as a sorting variable to identify financially constrained firms, with larger firms actually thought to be less constrained compared to smallerfirms, ceteris paribus.[6] At a minimum, if a firm's size captures mismeasurement of a firm's financial status, then we would expect the magnitude of the size effect for financially constrained firms to differ from that of financially unconstrained firms, ceteris paribus.

[6]Hennessy and Whited (2007) provide structural evidence that small firms face more costly external financing.

We identify financially constrained firms using the three most prominent empirical measures of a firm's financial status, namely the Kaplan-Zingales (1997), the Whited-Wu (2006), and the Hadlock-Pierce (2010) indexes.[7] We construct a series of dummy variables based on whether a firm ranks high or low in these indices and interact these dummies with the control variables and firm size. We also include the index itself as a control.[8] The interaction term between the financial status dummy and firm size estimates the difference the size/investment relationship between constrained and unconstrained firms. Table 4 reports the results. For comparison, specification (1) reports the baseline regression results without the financial status dummy. Specification (2) includes a dummy variable set equal to one if the firm's WW index is less than the median and zero otherwise. Specification (3) includes a dummy variable set equal to one if the firm's KZ index is less than the median and zero otherwise. Specification (4) includes a similar dummy variable, based on the median of SA index. Specifications (5) through (7) construct two dummy variables, with the first dummy set equal to one if the value of the respective indices is less than the first quartile of the distribution, and the second dummy is set equal to one if the value of the respective indices exceeds the third quartile of the distribution.

The results in Table 4 suggest that the size effect is unrelated to measures of financial status. The estimates of the size effect for high WW index and low WW index firms are statistically indistinguishable. The same results holds when the firms are sorted by the KZ index or the SA index. Column (5) shows that the size effect for firms in the top quartile of the WW index is not different from that of firms in the bottom quartile of the index. The results in Columns (6) and (7) are similar. To the extent that these indices capture the degree of a firm's external financing constraints, the results in Table 4 suggest that the negative relationship between firm size and investment rates does not reflect differences in financial status.

We perform further robustness analysis on these findings (results available upon request). Since the KZ index contains Tobin's Q and cash flow as components, there is some concern that the estimates reported in Table 4 may be biased as Q and cash flow enter the investment regression separately. Further, the presence of measurement error in Q can cause this bias to spill over to other regressors, because Q is correlated with

[7] The SA index, proposed by Hadlock and Pierce (2010), is defined as (-0.737*Size)+(0.043*$Size^2$)-(0.040*Age), where Size is the log of the inflation adjusted book value of assets and Age is the number of years a firm has been available on Compustat.

[8] For brevity, the interaction terms with Tobin's Q and cash flow as well as the coefficient on the dummy itself are not included in the table, but are available upon request.

all of the variables in the regressions. To address this issue, we strip Tobin's Q and cash flow out of the KZ index. Similarly, we exclude cash flow and firm size when computing the WW index, and firm size when computing the SA index. We then re-estimate the investment regression specifications reported in Table 4 using these pseudo KZ, WW and SA indexes. The unreported results are similar, suggesting that this concern does not drive the findings. Moreover, as an additional alternative to the KZ, WW and SA indexes, we use credit ratings to identify a firm's financial status. We classify firms with debt ratings as financially unconstrained because they are more likely to have greater access to external financing through capital markets. We consider firms without ratings as financially constrained. The unreported results are consistent with the findings in Table 4, suggesting that the negative relationship between firm size and investment rates does not reflect differences in financial status. We also confirm our findings on the relationship between the size effect and financial constraints in a larger unbalanced sample of firms.

3.2 Firm Size and Real Investment Opportunities

We now investigate whether firm size captures mismeasurement of a firm's true unobservable technological investment opportunity set. That is, whether firm size contains additional information about future investment opportunities that is not already incorporated in the standard proxies including Tobin's Q and cash flow.

If firm size truly reflects unobservable real investment opportunities, then the empirical findings would require larger firms to have lower investment rates because firms' marginal return to investment exhibit decreasing returns to scale in capital, ceteris paribus. If this was the case, we would expect, for instance, the firm scale coefficient β in (**??**) to depend positively on the degree of technological returns to scale in firms' operating profits with respect to capital. The higher the degree of returns to scale in firms' profits, the lower the sensitivity of the marginal profitability of capital, and thus of investment rate, to changes in the capital stock. Hence, the higher the degree of returns to scale, the lower in magnitude, and thus the less negative, the firm size estimate, β. We expect this same pattern to hold even conditional on imperfect control variables such as Tobin's Q and cash flow. We confirm these theoretical relationships using simulated data from a neoclassical model of investment in the section below.

In this section, instead, we empirically test for such a positive relationship between the degree of technological returns to scale and the firm size coefficients. To identify significant differences in the degree of technological returns to scale, we perform the empirical analysis at the two-digit SIC industry level. Since the main balanced panel of only 340 firms does not constitute a representative sample for all industries, we use instead a large unbalanced panel of 130,108 firms over the sample period 1962-2006 (see details in Appendix A). The longer time series and the larger number of firms in the unbalanced sample allow to better identify the variation in the degree of technological returns to scale across industries.

We first estimate the firm size coefficient β for each two-digit SIC industry using the investment specification in (**??**) including fixed effects. We estimate both unconditional and conditional size effect coefficients. We include Tobin's Q and cash flow in the set of control variables for the estimation of the conditional firm size coefficient. We then employ the methodology of Cooper and Haltiwanger (2006) to obtain estimates of the degree of technological returns to scale in capital, θ, by estimating a log-linear quasi-differenced regression of revenues on capital stock for each two-digit SIC industry. Appendix B provides details for the estimation of θ and the construction of the relevant variables. Both industry estimates of β and θ are obtained from a panel of firms within each industry using seemingly unrelated regressions. Table 5 reports the firm size and returns to scale point estimates and standard errors for each of the two-digit industries included in our sample.

We then estimate a cross-industry regression of the coefficients on firm size, β, on the estimates of technological returns to scale, θ. Table 6 reports the results including standard errors adjusted for the sampling variation in the generated regressors. Specifications (1) and (3) report the results for the unconditional and conditional firm size estimates, respectively. We find evidence of a positive relation between the firm size estimates β and technological returns to scale in capital, θ. This relationship is significant at conventional levels, even when accounting for the sampling variation in generated regressors.

We also estimate the firm size coefficients, β, and the technological returns to scale, θ, using aggregated industry-level data rather than firm-level data within industries. For each two-digit SIC industry, we compute the industry-level counterpart of the variables of interest. For example, the industry revenues are calculated as the sum of firm revenues within the industry for each year, and the industry investment rate is computed as the sum of firm investments divided by the sum of firm capital within the industry. As shown in specifications (2) and (4) of Table 6, the results are similar regardless of the estimation methodology.

The empirical evidence at the industry level confirms the existence of a relationship between the degree of the size effect in investment and and technological returns to scale. Overall, our findings suggest that firm size does capture information about a firm's decreasing technological returns to scale not fully accounted by standard empirical proxies such as Tobin's Q and cash flow. As such, firm size improves the measurement of a firm's unobservable investment opportunity set.

4 A Neoclassical Model of Firm Size and Investment

The empirical evidence suggests that firm size captures technological decreasing returns to scale rather than differences in financial status. We now focus on a Q-theory model of investment with no financial frictions and curvature in the profit function that generates a firm size effect consistent with the empirical results. We first present the model, then we proceed with its structural estimation via the simulated method of moments and assess its ability to quantitatively replicate the empirical findings.

4.1 Q-Theory of Investment with Curvature

We examine the optimal investment decision of a firm that maximizes the market value of current shareholders' wealth in the absence of any financing frictions. Without loss of generality, we assume that the firm is financed entirely by equity. The firm's per period profit function is $\pi(A,K)$, where K is capital and A is a profitability shock. The profit function $\pi(A,K)$ is continuous and concave, with $\pi(0,A) = 0$, $\pi_A(A,K) > 0$, $\pi_K(A,K) > 0$, $\pi_{KK}(A,K) < 0$ and $\lim_{K\to\infty} \pi_K(A,K) = 0$. We use the standard functional form

$$\pi(A,K) = AK^{\theta} \tag{1}$$

where $0 < \theta < 1$ captures the curvature of the profit function, which satisfies continuity, concavity and the Inada boundary condition. The reduced form profit function, $\pi(A,K)$, can be obtained from the firm's optimization over freely adjustable factors of production (see Appendix B). As such, the shock to the profit function, A, reflects variations in productivity, input prices and output demand. We can interpret the curvature of the profit function as reflecting the presence of decreasing returns to scale in production as in Gomes (2001), and/or firm market power as in Cooper and Ejarque (2003).

The profitability shock, A, follows a stationary first-order Markov process with transition probability $f(A',A)$, where a prime indicates a variable in the next period. We conveniently parameterize the shock process as AR(1) in logs:

$$\log\left(A'\right) = \mu(1-\rho) + \rho \log(A) + \varepsilon' \tag{2}$$

where $|\rho| < 1$ and ε' follows a (truncated) normal distribution with 0 mean, standard deviation of σ and finite support $\left[\underline{A}, \overline{A}\right]$.

The capital stock also lies in a compact set $\left[0, \overline{K}\right]$. As in Gomes (2001), we define $\overline{K}$ as:

$$\pi_K\left(\overline{A}, \overline{K}\right) - (r+\delta) \equiv 0$$

where $0 < \delta < 1$ is the capital depreciation rate and $r > 0$ is the opportunity cost of funds. $\overline{K}$ equates the maximum value of the marginal profitability of capital, $\pi_K\left(\overline{A}, \overline{K}\right)$, to the user cost of capital, $r+\delta$. As such, K always lies in the interval $\left[0, \overline{K}\right]$ because $K > \overline{K}$ is not economically profitable. The compactness of the state space and continuity of the profit function $\pi(A,K)$ ensure that $\pi(A,K)$ is bounded.

The firm purchases and sells capital, I, at a price of one and incurs standard quadratic adjustment costs that are given by

$$C(I,K) = \frac{\gamma}{2}\left(\frac{I}{K} - i^*\right)^2 K \tag{3}$$

where $\gamma > 0$. This specification implies that capital adjustment costs are non negative and minimized at the natural rate of investment i^*. As standard in the investment literature, we assume that the natural rate of investment, i^*, is equal to the depreciation rate, δ, implying that adjustment costs apply on net capital formation.

The firm chooses I each period to maximize the value of discounted expected future cash flows, V. The Bellman equation for the problem is:

$$V(K,A) = \max_{I} \left\{ \pi(A,K) - I - C(I,K) + \frac{1}{1+r} \int V\left(K',A'\right) d f\left(A',A\right) \right\} \tag{4}$$

where next period capital K' evolves as

$$K' = (1-\delta)K + I.$$

The first three terms in (4) represent the value of current equity distributions net of any securities issuance, and the last term represents the continuation value of equity. The assumptions above ensure that the dynamic model is well behavied and satisfies the conditions in Theorem 9.6 in Stokey and Lucas (1989) for the existence of a solution to the Bellman equation in (4).

4.2 Optimal Investment Policy

In this subsection we develop the intuition behind the model's ability to generate the size effect effect by examining its optimality conditions.

The firm chooses investment I using its conditional expectations of future profitability, A', and given the current capital stock, K. The optimal solution to the firm's problem in (4) satisfies the first-order condition with respect to I, which requires, at the optimum, the equivalence between marginal cost and benefit of investment:

$$1 + C_I(I,K) = \frac{1}{1+r} \int V_K\left(K',A'\right) d f\left(A',A\right). \tag{5}$$

The right side of this expression, which represents the marginal benefit of investment, is termed "marginal q". Given the operating profit function in (1) and the quadratic adjustment cost in (3), the optimal investment policy is then given by

$$\frac{I}{K} = i^* + \frac{1}{\gamma}\left[q(K,A) - 1\right]. \tag{6}$$

Our choice of quadratic adjustment costs makes the optimal investment policy in (6) consistent with the linear investment specification used for the empirical tests of size effects. The empirical specification, however, includes also an error term and fixed effects. These are often introduced in the model by allowing the adjustment cost function to include both fixed effects and a stochastic term through the natural rate of investment i^*. We opt instead for an alternative interpretation of the error term as measurement error since we pursue the implications of misspecification caused by the substitution of average for marginal q. Moreover, in order to render our simulated data comparable to the actual data, we remove unobserved heterogeneity from the actual data using fixed effects instead of introducing it in the model simulated data.

The presence of curvature in the profit function in an otherwise traditional investment model with quadratic adjustment costs violates the homogeneity conditions (Hayashi, 1982; Abel and Eberly, 1994). As such, marginal q differs from (average) Tobin's Q , which is now only an imperfect, yet observable, proxy. In addition, the violation of the homogeneity conditions makes marginal q not only a function of the profitability shock A (as it would be under homogeneity), but also of the capital stock, K. This dependence makes the capital stock itself a natural observable explanatory variable for investment, even in the presence of Tobin's Q.

With two state variables (A and K), Tobin's Q and the capital stock convey different information. When controlling for the capital stock, K, Tobin's Q, which is monotonically related to the profitability shock A, is likely to capture most of its variation. The significance of firm size in this case would therefore reflect the fact that in a world of many state variables a single variable like Tobin's Q may not capture all available information. In fact, the inclusion of firm size in a simple investment equation would improve the measurement of the underlying variation in marginal q, and hence in investment. Without any additional state variable, and consistent with the findings in Erickson and Whited (2000), we then generate cash flow effects by introducing classical measurement error in Tobin's Q.

4.3 Model Estimation

We solve the model numerically using standard value function iterations.[9] Given that there is no analytical representation for the model-implied moments, we estimate the model using the simulated method of moments (SMM) proposed by Lee and Ingram (1991). Specifically, we choose model parameters that set moments of artificial data simulated from the model as close as possible to the corresponding empirical data moments.

Following the empirical investment literature, we set the depreciation rate, δ, and the discount rate, r, to their conventional values of 0.15 and 0.05, respectively. These parameters are in line with the numerical values and estimates used in previous studies (Cooper and Ejarque, 2003; Hennessy and Whited, 2007). Given the general consensus concerning their numerical values, these parameters provide essentially no degrees of freedom for generating the quantitative results. We restrict the scaling parameter μ of the shock process in (2) so that the steady-state capital stock is normalized to 1.[10] We then estimate the following parameters: profit function curvature, θ; shock serial correlation, ρ; shock standard deviation, σ; and the capital adjustment cost, γ. We focus on the moments most directly related to the model parameters. Specifically, the moment vector includes the mean and variance of Tobin's Q, the variance and serial correlation of investment, and the variance of operating profit (cash flow).[11] Appendix C contains details concerning the choice of moments and the estimation of the model.

Table 6 presents the estimation results. Panel A reports the actual and simulated moments with t-statistics for the difference between the two. Panel B reports parameter point estimates, standard errors and a test of over-identifying restrictions (J-test) for the general specification. Taking into account the parsimony of our model, the J-statistic takes on a reasonably small value. The J-test does not provide rejection at the one percent level, implying that overall the model matches reasonable well the set of empirical moments viewed collectively, particularly when considering the low degrees of freedom. Most

[9]We first discretize the state space for the two state variables K and A following the procedure in Tauchen and Hussey (1991). We then solve the model via iteration on the Bellman equation (4), which produces the value function, $V(K,A)$, and the investment policy function, $I(K,A)$.

[10]In the steady-state, the capital stock is $K_{ss} = [\theta \exp(\mu) / (r+\delta)]^{1/(1-\theta)}$, which equates the marginal product of capital with its user cost, $r+\delta$.

[11]In simulations, one can see that the moments are quite responsive to variations in the values of the parameters.

simulated moments in Panel A match the corresponding data moments well, and all simulated moments are statistically indistinguishable from their empirical counterparts at conventional significance levels. Even if statistically insignificant, only the serial correlation of investment and the variance of Tobin's Q have simulated values that differ slightly from their corresponding values in the data. The serial correlation of investment in simulated data (0.27) is lower than its empirical counterpart (0.31). The quantitative gap between actual and simulated moments is not large, particularly when compared with the results in Cooper and Ejarque (2003), which fail to match this particular moment reporting a gap of at least 0.33. We attribute our improved performance mainly to a larger adjustment cost estimate, γ, of 1.13. Convex costs, which prevent firms from swiftly investing in response to persistent productivity shocks, imply investment that is positively autocorrelated with many relatively small adjustments. Hence, higher γ generates more serially correlated investment so that firms optimally economize on the costs of capital adjustment. An even larger adjustment cost would certainly increase the serial correlation of investment, but at the expense of a less volatile investment series.

The high variance of Tobin's Q in the data (0.41) exceeds only slightly its simulated counterpart (0.38). Matching the high variance of Tobin's Q, which also drives our large adjustment cost estimate, is notoriously difficult for most adjustment-cost models. For instance, Eberly, Rebelo and Vincent (2011), who exclude the variance of Tobin's Q from their target moments, report a gap of about 0.30. As emphasized in Erikson and Whited (2000), a potential additional source of volatility is measurement error in Tobin's Q.[12] In the next subsection, we follow their lead and incorporate measurement error in Tobin's Q to generate a cash flow effect in investment regressions. Our choice to include the variance of Tobin's Q among the set of target moments, despite its challenges, naturally provides useful additional restrictions on plausible values for the magnitude of measurement error in Tobin's Q.

The quadratic adjustment cost parameter, γ, has received enormous attention in the literature since a regression of investment rates on measures of average or Tobin's Q identifies this parameter when the

[12] Additional sources of volatility in Tobin's Q can also be attributed to differences between the intrinsic value and the market value of equity. Some supporting evidence can be found, for instance, in measures of Q that do not rely on the market value of equity and perform better than traditional ones in explaining investment. These alternative measures include estimates based on cash-flow forecasts (Abel and Blanchard, 1986; Gilchrist and Himmelberg, 1995), analyst forecasts of earnings growth (Cumins, Hassett, and Oliner,2006), and bond prices (Philippon, 2009).

operating profit and the cost of capital adjustment are linearly homogeneous. Using the Q-theoretic approach, estimates of γ range from over 20 as in Hayashi (1982) to as low as 3 in Gilchrist and Himmelberg (1995). One noticeable exception is the recent study by Hall (2002) in which he estimates average (across industries) quadratic capital adjustment costs of about 0.91. While direct comparison with other estimates should be viewed with caution given differences in methods and datasets, our estimate of 1.13 is comparable to previous studies, though higher than the estimates of 0.17-0.23 reported in Cooper and Ejarque (2003). The inclusion of the high variance of Tobin's Q among the set of target empirical moments, along with the reasonably good match of the high serial correlation of investment in the data, are mainly responsible for our understandably larger estimate of γ.

Our estimate of the curvature of the profit function, θ, is 0.91. Despite differences in estimation methods and datasets, this value is consistent with estimates reported in previous studies. For instance, Burnside (1996) estimates a value of 0.80 for the average degree of returns to scale across industries. More recently, DeAngelo, DeAngelo and Whited (2011) estimate a value of 0.79 using a more complex dynamic model of investment and capital structure decisions. Differently from Cooper and Ejarque (2003), who estimate a value of 0.70, the larger estimate in our dataset is consistent with the lower average value of Tobin's Q. Despite its relatively higher value, our estimate of θ also confirms the existence of substantial technological decreasing returns to scale.

The point estimate of the serial correlation (ρ) and standard deviation of profit shocks (σ) are 0.46 and 1.04, respectively. These values are qualitatively comparable with estimates displayed in previous studies. For instance, our estimate of the standard deviation of profit shocks (σ) is close to the value of 0.90 reported in Cooper and Ejarque (2003), though is generally higher than values reported in more recent studies, which estimate directly these parameters using only moments of the empirical distribution of operating profit (Hennessy and Whited, 2007; DeAngelo, DeAngelo and Whited, 2011). Our higher estimates, instead, are not only driven by the high volatility of operating profits, but also, and most importantly, by the high empirical variance of Tobin's Q.

While it is unlikely that our relatively simple model provides a complete description of the empirical relation between investment and *all* its determinants, it delivers overall a fairly good parsimonious approximation given the focus of the paper on generating the properties of investment from technological decreasing returns to scale.

4.4 Simulated Investment Regressions

In this section we investigate the model ability to generate quantitatively the size effects found in corporate investment data. We report the simulation results in Table 7. For easy of comparison, we also include their empirical counterparts from Table 2.

As shown in Panel A of Table 7, the coefficient estimate of the regression of investment rate on firm size is -0.05 in simulated data versus its empirical counterpart of about -0.07. Hence, the unconditional size effect, which arises because of decreasing returns to scale, is similar and significant in both simulated and empirical data.

Given the model-implied linear investment equation, a regression with three variables, Tobin's Q, cash flow and size, all highly correlated to the two only state variables, A and K, would not reproduce in simulations a size effect conditional on *both* Tobin's Q and cash flow comparable to the data. For instance, given firm size and Tobin's Q, cash flow would be informationally redundant in simulated investment regressions. Therefore, in order to generate also a cash flow effect as in the data, we follow Erickson and Whited (2000), and allow for classical measurement error in Tobin's Q.[13,14]

As emphasized in Erickson and Whited (2000), classical measurement error in Tobin's Q naturally generates a cash flow effect in investment regressions, even when Tobin's Q is a sufficient statistic for investment - i.e. under linear homogeneity assumptions. Hence, in our inhomogeneous investment model, where marginal q rather than Tobin's Q is a sufficient statistic for investment, measurement error in Tobin's Q allows to generate a sizeeffect conditional on *both* Tobin's Q and cash flow as in the data, rather than a size effect conditional on *either* Tobin's Q *or* cash flow only.

[13]The introduction of measurement error in Tobin's Q to generate cash flow effects is also consistent with the empirical evidence reported in Table A.2**.** Applying the reverse regression methodology in Erickson and Whited (2005), we find that, also in our data, the cash flow effect is particularly sensitive to measurement error in Tobin's Q.

[14]Alternatively, one could generate a cash flow effect by introducing financial frictions as in Gomes (2001) and Hennessy, Levy and Whited (2007). We opt, instead, for measurement error in Tobin's Q given our aim of showing how size effects naturally arise from the curvature of the profit function, even in the absence of financial frictions.

Specifically, we suppose that the econometrician observes Tobin's Q with error, $\widetilde{Q} = Q + \varepsilon$, where $\varepsilon \sim N\left(0, \sigma_{\varepsilon}^{2}\right)$. We then set σ_{ε}^{2} equal to a proportion, x, of the variance of the true Q**.** Panel B of Table 7 reports the results for different values of the variance of measurement error, x. The inclusion of the variance of Tobin's Q among the set of target moments for the estimation of the structural parameters imposes discipline over the plausible range of values for x. Given the variance of Tobin's Q of 0.378 in simulated data, a plausible value for the upper bound on x can be obtained by allowing for an increase, $0.378 \times (1+x)$, that matches the upper bound of the 95 percent confidence interval of the empirical variance of Tobin's Q, 0.482 (= $0.414 + 1.96 \times 0.035$). We set the upper bound on x to a conservative value of 0.25, which is slightly below such a number, 0.28 ($\simeq 0.482/0.378 - 1$), and still an order of magnitude smaller than the value implied by Erikson and Whited (2000).

Our natural benchmark for x is 0.10, which brings the simulated variance of Tobin's Q, 0.38, close to the empirical one, 0.41.[15] The coefficient on firm size, conditional on Tobin'Q and cash flow, is about a significant -0.042 in simulated data, and very close to its empirical counterpart of -0.050. The coefficients on Tobin's Q and cash flow are also significant and comparable to their empirical counterparts.

Within the plausible range of values for the variance of measurement error, the model-implied investment regressions generate conditional size effects very similar to the data. The coefficient on Tobin's Q decreases monotonically with the variance of measurement error from 0.087 to 0.035. Even though there are multiple regressors, this pattern is consistent with the evidence on the attenuation bias in the estimation of capital adjustment costs using mismeasured Tobin's Q (Erickson and Whited, 2000; Cooper and Ejarque, 2003). The coefficient on cash flow increases substantially with the variance of measurement error and ranges from 0.166 to 0.246. The high sensitivity of cash flow to measurement error in Tobin's Q is also consistent with previous findings in Erickson and Whited (2000, 2005). The coefficient on firm size, instead, decreases only slightly with the variance of measurement error from -0.042 to -0.064. These findings concerning the sensitivity to measurement error in Tobin's Q are also in line with our empirical investigation. Applying the reverse regression methodology in Erickson and Whited (2005), whose results

[15] Gomes (2001) also uses a value for the variance of the measurment error equal to 1/10 of the variance of Q.

are reported in Table A.2 in Appendix A, we confirm that the size effect is substantially less sensitive, and as such more robust, than the cash flow effect to measurement error in Tobin's Q.

4.5 *Simulated Variance Decomposition*

We now investigate further the quantitative implications of our simple neoclassical model with a variance decomposition of investment. Table 8 compares the variance decomposition of investment in simulated and actual data. In order to make the actual results comparable to our simulations, which produce i.i.d. firms, we remove unobserved heterogeneity from the actual data by using fixed firm and year effects. Hence, we report the *within* variance decomposition for the regression in actual data. We normalize the Type III partial sum of squares for each effect by the aggregate partial sum of squares across all effects in the regression specification, so that each column sums to one.

In our simulated data, the only sources of error in the investment regression consist of mismeasurement in marginal q and classical measurement error in Tobin's Q. As such, the adjusted R^2 for the investment regression in simulated data of about 0.55 naturally exceeds its corresponding value of 0.22 in actual data.[16] Most importantly, however, the relative contribution of each variable to the variance of investment both in simulated and actual data are fairly similar. In our natural benchmark with modest amount of measurement error ($x = 0.10$), about 41% of the explained variation in investment can be attributed to Tobin's Q alone versus 31% in actual data. As expected, the noisier the measure of Tobin's Q, the lowerits contribution to the variance of investment. About 45% of investment variation in simulated data can instead be attributed to cash flow versus 42% in actual data. The cash flow variable becomes relatively more important with substantial measurement error in Tobin's Q. Firm size contributes about 14% of investment variation in simulated data against 27% in actual data. While still lower than its empirical counterpart, the size contribution increases up to 17% with the measurement error in Tobin's Q. Consistent with our empirical investigation of the impact of measurement error in Tobin's Q, the contribution of firm size is much less sensitive than cash flow to measurement error in Tobin's Q.

[16] The introduction of additional shocks, for instance, stochastic shocks to adjustment costs, which are commonly used in the investment literature, and/or different curvature of the adjustment cost function would contribute towards a reduction of the R^2 for the investment regression in simulated data.

While it is unlikely that our parsimonious investment model provides a complete description of all the shocks underlying the investment dynamics in actual data, it still yields a reasonably good approximation.

4.6 Firm Size and Technological Returns to Scale

In this section we investigate in simulated data the relation between the curvature of the operating profit function, θ, and the size effect estimate, β. This relation underlies the identification of the firm size effect arising from technological returns to scale and supports our cross-industry empirical analysis above.

Table 10 reports the size coefficient estimates in simulated data for different values of the curvature of the profit function, θ. Panel A provides the estimate from a regression of investment rate (I/K) on firm size ($\ln K$) only. The higher the operating profit curvature, θ, the higher (less negative) the size effect estimate, β. In the absence of any other variable, firm size effectively captures the marginal profitability of capital. With decreasing returns to scale, the higher the current capital stock, the lower the marginal return to capital and hence the lower the equilibrium investment rate, ceteris paribus. How much lower is the marginal return to capital, and hence investment rate, depends on the operating profit curvature, θ. The higher θ, the lower the sensitivity of the marginal return to capital, and thus investment rate, to changes in the capital stock. Hence, the higher the curvature θ, the lower in magnitude the size effect estimate, β. As θ approaches constant returns to scale ($\theta \rightarrow 1$), the marginal return to capital becomes insensitive to changes in the capital stock, and any size effect progressively dissipates ($\beta \rightarrow 0$).

Panel B of Table 9 provides the conditional size effect estimates from a regression of investment rate (I/K) on firm size ($\ln K$), cash flow ($/K$) and Tobin's Q (V/K), for various levels of measurement error in Tobin's Q. The same pattern between the operating profit curvature, θ, and size effect estimates holds even conditional on imperfect control variables such as Tobin's Q and cash flow. As such, firm size complements any information about decreasing return to capital already incorporated in these imperfect controls. The noisier the measure of Tobin's Q, the stronger the size effect as firm size becomes relatively more informative about the marginal return to capital, ceteris paribus. As the curvature approaches constant returns to scale ($\theta \rightarrow 1$), Tobin's Q becomes a sufficient statistic for investment, the marginal return to capital becomes insensitive to changes in the capital stock, and the conditional size effect coefficients approach zero ($\beta \rightarrow 0$). The less noisy the Tobin's Q, the faster the size effect approaches zero.

5 Conclusion

A large literature in economics has investigated the determinants of firm growth dynamics. On one side, the industrial organization and growth literature have focused on the role of firm size, on the other side, the corporate finance literature has focused on the role of Tobin's Q and cash flow. This paper links the two streams of literature and examines whether size dependence is important in corporate investment decisions even after controlling for standard proxies for firm investment opportunities and financial status.

The results of our empirical analysis provide robust evidence that small firms invest significantly more than large firms even after controlling for Tobin's Q and cash flow. We find that firm size is at least as important as Tobin's Q and cash flow, both economically *and* statistically, in explaining variation in corporate investments. Interestingly, the size effect is more robust to measurement error in Tobin's Q than the cash flow effect. Furthermore, the empirical evidence suggests that the firm size effect reflects the mismeasurement of firms' unobservable real investment opportunity set rather than reflecting differences in firms' financing frictions.

Consistent with the empirical evidence, we confirm that a simple Q-theory model of investment with curvature in the profit function and capital adjustment costs can replicate quantitatively the empirical findings of a firm size effect in corporate investment. As such, even a simple model with no financial frictions, which realistically departs from the traditional homogeneity assumptions, recommends the use of firm size to explain first-order variation in investment.

Appendix

This section contains three appendices with details about the robustness tests on the empirical analysis, estimation of technological returns to scale, and SMM estimation of the model.

Appendix A

In this appendix we discuss in more detail the data sets used for the empirical analysis and the robustness tests on the size effect findings.

A.1 Data

We construct three samples of firms for the empirical analysis. The unbalanced sample of US firms is taken from the combined annual research, full coverage, and industrial COMPUSTAT files for the years 1962 to 2006. We omit utilities (SIC 4900–4999) and financial firms (SIC 6000-6999) from the sample. We keep all firm-years in our main sample that have non-missing information available to construct the primary variables of interest, namely investment in property, plant and equipment, total capital (net property, plant and equipment), book value of total assets, market value of assets (book value of assets plus the market value of common stock minus the book value of common stock), earnings before extraordinary items, depreciation, stock price at the fiscal year close, and the number of common shares outstanding. We deflate capital expenditures and net property, plant and equipment by the deflator for non-residential investment from the NIPA tables. The remaining data items are deflated using the consumer price index. To ensure that our measure of investment captures the purchase of property, plant and equipment, we eliminate any firm-year in which a firm in the sample made a major acquisition. We then trim the variables (investment rates, Q, cash flow rate) at the 1st and 99th percentiles of their distributions to reduce the influence of outliers, which are common in accounting ratios. This procedure yields a sample of 130,108 firm-years representing 13,986 different firms.

We also construct a sample of US firms in a balanced panel. To be included in the balanced sample, a firm must have sufficient data available to measure Tobin's Q, investment, cash flow, and capital stock for every year from 1980 to 2006. In addition, to ensure that our measure of investment captures purchases of property, plant and equipment, we eliminate any firm that may have made a major acquisition during the sample period. These criteria yield a sample of 9,180 firm-years composed of 340 firms that have data available in each of the 27 years in the sample period.

Our last sample is composed of international firm level data from Thomson Financial's Worldscope database. Worldscope provides the broadest coverage of international data, covering companies in more than 50 developed and emerging markets and accounting for more than 96 percent of the market value of publicly traded companies across the globe. We use data on firms from Australia, Brazil, Canada, France, Germany, Japan, South Korea and the United Kingdom for our international sample as these eight countries have the widest coverage for non-US firms in the Worldscope database. We keep all firm-years in each of these countries with non-missing data for investment rates, Tobin's Q, cash flow and net property plant and equipment. The international sample has 62,745 firm-years composed of 10,839 firms over the period 1980 to 2005.

Table A.1 reports summary statistics of the main variables of interest for the unbalanced sample, balanced sample and international sample of firms. Overall, our variables of interest are comparable with previous studies, except for the slightly higher mean investment rate due to the scaling of capital expenditures by net property, plant and equipment rather than gross property, plant and equipment or total assets.

A.2 Robustness

We now conduct a large battery of robustness tests to address common concerns associated with the estimation of investment regressions.

Measurement error. A potential concern with the interpretation of the tests for size effects is the presence of measurement error in Tobin's Q. We now investigate whether classical measurement error in our proxy for Tobin's Q affect our estimates. In our first approach, we employ a classical errors-in-variables methodology by instrumenting for Tobin's Q. We use two sets of instruments: (i) lagged cash flow; and (ii) lagged cash flow and lagged Tobin's Q. The results of the instrumental variables estimation are reported in the first two columns of Table A.2. In both cases, the magnitude and statistical significance of the firm size is virtually no different from previous results.

As a second approach, we investigate whether the quality of our proxy for Tobin's Q can explain the consistently negative coefficient we obtain on firm size in the investment regressions. To test whether measurement error is driving the sign of the coefficient on firm size, we employ the methodology of Erickson and Whited (2005). This method allows a researcher to draw inferences about the signs of coefficients in the presence of a mismeasured regressor. The third column of Table A.2 reports the results of the reverse regression in the methodology of Erickson and Whited (2005), whereby we regress the proxy for Tobin's Q on investment, cash flow, and firm size. We confirm that the coefficient on firm size in this reverse regression maintains its negative sign, suggesting that the possible measurement error in our proxy for Tobin's Q is not responsible for the negative sign of the coefficient in the baseline investment regression. Interestingly, the sign on the cash flow coefficient switches from positive to negative in the reverse regression, suggesting that the cash flow sensitivity of investment is sensitive to measurement error in Tobin's Q.

As a third approach, we use an alternative measure of Tobin's Q proposed by Cummins, Hassett and Oliner (2006), which employ firm-specific earnings forecasts from securities analysts rather than stock market values. We follow this approach and estimate the numerator for Tobin's Q using IBES analysts' consensus earnings forecasts. Similar to Cummins et al (2006), our sample period is 1982 to 1999. We further require that each firm included in the final sample have at least two consecutive years of non-missing data. The fourth column of Table A.2 reports the results of the investment regression with the analyst-based estimate of Tobin's Q. We find that the magnitude and statistical significance of firm size is similar to the estimates from the regression with the stock-market based Tobin's Q.

Selection bias. Given that our sample is made up of publicly traded firms from Compustat, a potential concern is that the results may be due to sample selection bias. Specifically, while small and fast growing firms are more likely to enter and remain in Compustat over time, small firms initially in the database that did not experience growth over time are more likely to exit. Hence, our inability to observe these small firms exiting the database may create a bias in favor of our findings. However, the Compustat database, which includes only firms with publicly traded securities, is also more likely to represent mostly the large firms with good growth prospects in the overall economy. Hence, the left-truncation of the true size distribution of all firms in the economy as represented in our sample may bias against finding evidence of a size effect given that only firms that are likely to be larger and have higher growth rates will be included in the sample. Overall, the direction of these biases may work in favor as well as against our findings.

We use a two-stage Heckman-type procedure to control for sample selection bias. We first model the exit decision of firms in the large unbalanced panel as a function of firm size, Tobin's Q, cash flows, cash holdings, and leverage. We then obtain the inverse Mill's ratio and include it on the right hand side of the conditional investment regression. Specification (5) in Table A.2 reports the results. Controlling for selection bias does not affect our findings.

Timing of variables. In the baseline regression we scale end-of-year investment by beginning-of-year capital on the left hand side, and include the log of beginning-of-year capital on the right hand side of the regression. One potential concern is that the negative coefficient on log of firm size may be mechanically driven. In response, we replace $\log K_{i,t-1}$ with $\log K_{i,t-2}$ in the investment regression. As shown in specification (1) of Table A.3, the economic and statistical significance of firm size remains unaffected.[17]

Since we use beginning-of-year Tobin's Q and lagged cash flow to explain end-of-year investment, our proxy variables might only partially reflect changes in the investment opportunities and/or financial status occuring over the year. Specification (2) reports estimates including contemporaneous Tobin's Q and cash flow. Controlling for the change in Q and cash flow over the investment period does not affect the significance of firm size.

Our measure of future investment opportunities and/or financial status might be inadequate if there are lags between when a firm has investment opportunities and when the actual investment is measured. These lags may be due to accounting practices as well as time-to-build considerations. The next specification include additional lags of Tobin's Q and cash flow in response. Firm size still preserves its economic and statistical significance.

We conclude that the timing of our proxy variables for investment opportunities and/or financial status has no effect on the results.

[17]We obtain similar results when using $\log K_{i,t-k}$, for $k = 3,4,5$, either in place of or as instrument for $\log K_{i,t-1}$.

Omitted variables. The size effect may result because of omitted variables potentially capturing investment opportunities and/or financial status. For instance, Eberly, Rebelo and Vincent (2011) provide evidence that lagged investment is an important determinant of investment. Specification (4) reports the results of the conditional investment regression including lagged investment. Since the lagged dependent variable is correlated with the firm fixed effect, we employ the Arellano-Bond dynamic panel estimator to obtain consistent estimates. Consistent with the evidence in Eberly, Rebelo and Vincent (2011), the coefficient on lagged investment is significant and positive. However, controlling for lagged investment does not affect the significance of firm size.

Early studies by Evans (1987) and Hall (1987), and more recently by Cooley and Quadrini (2001), discuss the evidence of firm growth dependence on both firm size and firm age. Following Fama and French (2001) and Pastor and Veronesi (2003), we proxy for a firm age using the number of years since a firm became public. As shown in specification (5), the inclusion of firm age does not affect our findings.

In specification (6), we include additional control variables for a firm's financial status. Following Lang, Ofek and Stulz (1996), and Kaplan and Zingales (1997), we include the following controls: cash holdings, defined as cash and short-term investment scaled by total assets; leverage, defined as the sum of short-term and long-term debt scaled by total assets; return on assets, defined as net income scaled by total assets; and a dividend payer dummy set equal to one if the firm pays a cash dividend in a given year. We note that the inclusion of these additional controls does not change the magnitude or significance of firm size.

Nonlinear specifications. In specification (7), we investigate whether firm size is picking up non-linearities in the relationship between investment and Tobin's Q and cash flow. We estimate a complete second order polynomial in these variables. Specifically, we include (but do not report for brevity) squared terms of the control variables, as well as their interactions. The results in Table A.3 show that the inclusion of high-order polynomials does not affect the magnitude or significance of firm size.

Alternative samples. In specification (8) of Table A.3, we report the converge estimates based on a large unbalanced panel of US firms from Compustat for the period 1962-2006. We confirm the presence of a size effect in the unbalanced sample.

We also investigate the presence of size effects in eight other countries. From the Worldscope database, we obtain firm level data for the period 1980-2005 for Australia, Brazil, Canada, France, Germany, Japan, South Korea, and the United Kingdom. The investment regressions for each international sample are reported in Table A.4. We confirm that in each of the eight countries, there is significant evidence of size effects comparable to that found in the US data. Therefore, we conclude that our findings are not limited to the sample of US firms.

Additional robustness. We consider, but do not report for brevity, a number of additional robustness tests: (1) we run investment regressions over different sub-samples; (2) to reduce the influence of outliers we deflate investment and cash flow by total assets rather than capital; (3) we trimmed relevant firm variables at different percentiles of their unconditional distribution; (4) we include firms with negative investments and firm-years observations with large acquisitions; (5) we use the change in net property, plant and equipment instead of capital expenditures to measure investment; (6) we add the leasing of property, plant and equipment to capital expenditures as an alternative measure of investment. The main results are statistically robust. In addition, we obtain similar findings across alternative estimation methodologies including (1) OLS with firm and year fixed effects estimated by first differencing the actual observations, and (2) Fama-MacBeth (1973) regressions.

Appendix B

In this section, we discuss the measurement and estimation of technological returns to scale. We first derive the profit function, and then we discuss the estimation details.

B.1 Measurement of Technological Returns to Scale

We assume that each productive unit has a Cobb-Douglas production function given by $y = zK^{\alpha_K}L^{\alpha_L}$. z denotes the productivity shock, K is physical capital, L is the variable factor(s), and ω is the price of the variable factor(s). The equations that follow are based on one variable factor for expositional purposes but extend easily to multiple variable factors. We furthermore assume that the inverse demand function with constant elasticity is given by $p = \varepsilon y^{-\eta}$ with corresponding revenue function of $R(y) = y^{1-\eta}$, where ε denotes a demand shock. Optimization of the profit function over the variable factor

$$\max_{L}\left[R(y) - \omega L\right]$$

yields a revenue function $R(A,K)$ and profit function $\Pi(A,K)$ given by

$$R(A,K) = \frac{A}{1-\phi}K^{\theta} \tag{7}$$

and

$$\Pi(A,K) = AK^{\theta} \tag{8}$$

where $A = (1-\phi)\left[\varepsilon z^{(1-\eta)}\left(\phi/\omega\right)^{\phi}\right]^{1/(1-\phi)}$ reflects shocks to the production function, output demand and variations in variable factors' costs, $\theta = \alpha_K(1-\eta)/(1-\phi)$ and $\phi = \alpha_L(1-\eta)$. There are decreasing technological returns to scale, $\theta < 1$, as long as $(\alpha_K + \alpha_L)(1-\eta) < 1$. Even with inelastic demand function ($\eta = 0$), the presence of decreasing returns to scale in production, $\alpha_K + \alpha_L < 1$, is sufficient to generate curvature in the profit function, $\theta < 1$.

The coefficient on K measuring the degree of returns to scale in capital (θ) in both the revenue and profit functions is the same. Moreover, the properties of the shocks to revenue and profits are the same up to a factor of proportionality. Hence, we can estimate θ from either a log-linear profit or revenue regression on the capital stock. We opt for the latter since there is potentially less measurement error involved. There are a small number of observations with negative measured real variable profits but by construction there are no businesses with negative real revenue. In the analysis in the paper we report the estimate of θ from the real revenue regression, but this is not critical for the reported results. Real revenues are measured as total sales, deflated by the consumer price index from NIPA.

B.2 Estimation of Technological Returns to Scale

We follow closely Cooper and Haltiwanger (2006) to estimate the curvature parameter θ. We refer to profit or revenue functions interchangeably because they only differ for a factor of proportionality. In the following analysis, we use the subscripts i and t to denote firm and time, respectively. We use lower case letters to denote the logs of the corresponding upper case variables.

Let $a_{it} = \ln(A_{it})$ have the following structure

$$a_{it} = \gamma_t + \varepsilon_{it}$$

where γ_t is a common shock, and ε_{it} is a firm-specific shock, whose dynamics are given by

$$\varepsilon_{it} = \eta_i + \rho_\varepsilon \varepsilon_{it-1} + \omega_{it}$$

where $\omega_{it} \sim MA(0)$ and η_i is a firm-specific time-invariant effect capturing heterogeneity in the average firm profitability shocks. Taking logs and quasi-differencing the profit equation in (8) yields

$$\pi_{it} = \rho_\varepsilon \pi_{it-1} + \theta k_{it} - \rho_\varepsilon \theta k_{it-1} + \gamma_t - \rho_\varepsilon \gamma_{t-1} + \eta_i + \omega_{it}$$

or

$$\pi_{it} = \beta_1 \pi_{it-1} + \beta_2 k_{it} + \beta_3 k_{it-1} + \gamma_t^* + \eta_i + \omega_{it}$$

where $\beta_1 = \rho_\varepsilon$, $\beta_2 = \theta$, $\beta_3 = -\rho_\varepsilon \theta$, and $\gamma_t^* = \gamma_t - \rho_\varepsilon \gamma_{t-1}$.

Whenever the standard assumption on the initial conditions hold ($E[x_{i1}\omega_{it}] = 0$ for $t = 2, ..., T$), then by first differencing, we have

$$E[x_{it-s}\Delta\omega_{it}] = 0$$

where $x_{it} = (k_{it}, \pi_{it})$ for $s \geq 2$. This allows the use of suitably lagged levels of the variables as instruments, after the equation has been first-differenced to eliminate the firm-specific effects (Arellano and Bond, 1991) as:

$$\Delta\pi_{it} = \beta_1 \Delta\pi_{it-1} + \beta_2 \Delta k_{it} + \beta_3 \Delta k_{it-1} + \Delta\gamma_t^* + \Delta\omega_{it}\,.$$

We estimate this equation via 2SLS estimator using a complete set of time dummies to capture the aggregate shocks and using lagged and twice-lagged capital and twice-lagged profits as instruments. The estimation of θ is performed for each two-digit SIC industry separately.

Appendix C

This appendix provides details concerning the estimation of the model and the choice of moments.

C.1 Model Estimation

We follow closely the estimation procedure in Lee and Ingram (1991) and estimate the structural parameters of the model using the simulated method of moments (SMM). First, we estimate a set of selected data moments, $\widehat{\Phi}_N$, using an empirical sample of length N. Without loss of generality, the selected data moments can be represented as the solution to the maximization of a criterion function

$$\widehat{\Phi}_N = \arg\max_{\Phi} J\left(Y_N, \Phi\right)$$

where Y_N is a data matrix of length N. Then, we construct S data sets based on simulations of the model under a given parameter vector ν. For each simulated data set s, we estimate the corresponding selected moments, $\widehat{\phi}_n^s(\nu)$, as the solution to the maximization of an analogous criterion function:

$$\widehat{\phi}_n^s(\nu) = \arg\max_{\phi} J\left(y_n^s, \phi\right)$$

where y_n^s denotes a simulated data matrix of lengh n.The SMM estimator of the parameter vector ν minimizes the distance between the selected empirical and simulated moments as

$$\widehat{\nu} = \arg\min_{\nu} \widehat{G}_N' \widehat{W}_N \widehat{G}_N$$

where $\widehat{G}_N \equiv \left[\widehat{\Phi}_N - \frac{1}{S}\sum_{s=1}^{S}\widehat{\phi}_n^s(\nu)\right]$ and $\widehat{W}_N$ is an arbitrary positive definite matrix that converges in probability to a deterministic positive definite matrix W. The optimal weighting matrix is

$$\widehat{W}_N = \left[N\, var\left(\widehat{\Phi}_N\right)\right]^{-1}. \tag{9}$$

Given that the selected empirical moments, $\widehat{\Phi}_N$, can be represented as ordinary least squares regression coefficients, we estimate their variance-covariance matrix using the seemengly unrelated regression approach. Specifically, we first estimate each regression separately using ordinary least squares, which provides consistent estimates for each moment as well as regression disturbances. Then, we estimate the variance-covariance matrix, $var\left(\widehat{\Phi}_N\right)$, allowing for heteroskedestacity and cross-correlation among firms in the panel as well as for correlation across regressions.

We solve the model using value-function iteration and simulate 10 artificial panels of 340 independent and identically distributed firms each with 270 years of data. We compute the simulated moments using the last 27 years of simulated data, which corresponds to the time span of the balanced sample from Compustat.[18,19] The indirect estimator is asymptotically normal for fixed S:

$$\sqrt{N}\left(\widehat{\nu} - \nu_0\right) \xrightarrow{d} \mathcal{N}\left(0, Avar\left(\widehat{\nu}\right)\right)$$

with the asymptotic variance-covariance matrix of the estimated parameters

$$Avar\left(\widehat{\nu}\right) = \left(1 + \frac{1}{S}\right)\left[\Pi' W \Pi\right]^{-1}$$

where $\Pi = \text{plim}_{N\to\infty}\, \partial\widehat{G}\left(\nu_0\right)/\partial\nu'$ and $W = \left[N var\left(\widehat{\Phi}\left(\nu_0\right)\right)\right]^{-1} = \left[N var\left(\widehat{\phi}\left(\nu_0\right)\right)\right]^{-1}$. We estimate Π by numerically differentiating $\widehat{G}\left(\widehat{\nu}\right)$ with respect to ν, and W by using $\widehat{W}_N$ as in (9). Further, we perform a test of the overidentifying restrictions of the model, with

$$\frac{NS}{1+S}\widehat{G}_N' \widehat{W}_N \widehat{G}_N \xrightarrow{d} \chi^2_{\dim(\Phi)-\dim(\nu)}$$

[18] We consider only the last part of the series to avoid the influence of a possibly suboptimal starting point.

[19] Michaelides and Ng (2000) point out that good finite-sample performance of an indirect inference estimator requires a simulated sample that is approximately ten times as large as the actual data sample.

where the χ^2 distribution has degrees of freedom equal to the dimension of selected moments, $\dim(\Phi)$, minus the dimension of parameters, $\dim(\nu)$.

Finally, we verify the properties of our SMM estimation procedure by using a simple robustness check. Starting with a known parameter vector, $\overline{\nu}$, we simultate a panel of firms and compute the seleceted simulated moments, $\widehat{\phi}(\overline{\nu})$. We then use the SMM procedure described above to fit these moments and recover the true parameter vector $\overline{\nu}$ (which generated the data). Failure to recover the true parameters may indicate lack of identification of the model parameters or inadequate estimation procedure. We find that our estimation procedure can recover reasonably well the true parameter vector, $\overline{\nu}$, even across SMM runs with different starting values.

C.2 Choice and Estimation of Moments

We choose the following five moments to match: the mean and variance of Tobin's Q, the variance and serial correlation of investment, and the variance of operating profit (cash flow). All of the model parameters affect all of these moments in some way. The variance of operating profit (cash flow) helps identify the shock variance, σ. Higher σ produces more volatile operating profit. The variance of investment rate helps identify both the curvature of the profit function, θ, and the adjustment cost parameter, γ. Lower θ and higher γ produce less volatile investment. The serial correlation of investment contributes to identify the shock serial correlation, ρ, and the adjustment cost parameter, γ. Higher ρ and γ generate more serially correlated investment because of the convex capital adjustment costs. The mean of Tobin's Q is primarily informative about the curvature of the profit function, θ. Lower θ produces higher Tobin's Q, ceteris paribus. The variance of Tobin's Q is mainly informative about the shock variance, σ, and the adjustment cost parameter, γ. Higher σ and γ generate more volatile Tobin's Q, ceteris paribus.

One final issue concerns the estimation of the empirical moments given the presence of unobserved heterogeneity in our data from Compustat. Since our simulations produce i.i.d. firms, in order to make our simulated data comparable to our actual data, we can either add heterogeneity to the simulations, or remove the heterogeneity from the actual data. We opt for the latter approach using firm and year fixed effects in the estimation of our empirical moments.

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Table 1
Investment Rates by Size Deciles

This table reports mean investment rates and corresponding standard errors across firm size deciles. Portfolios are formed each year by allocating firms into size deciles. We report an equal-weighted average of firm investment rates. The sample period is 1980 to 2006.

Size Decile	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mean	0.333	0.276	0.246	0.237	0.225	0.229	0.212	0.199	0.201	0.170
Std. Error	0.010	0.007	0.005	0.005	0.004	0.004	0.004	0.003	0.003	0.003

Table 2
Firm Size and Corporate Investment

This table reports estimates from regressions of the type:

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_i + \beta \log K_{i,t-1} + \phi X_{i,t-1} + \gamma_t + \varepsilon_{it},$$

where the left-hand-side is end-of year capital expenditures scaled by beginning-of-year property, plant and equipment. The right-hand-side variables include firm fixed effects, α_i, year fixed effects, γ_t, $\log K_{i,t-1}$ is the natural logarithm of beginning-of-year capital stock, and $X_{i,t-1}$ denotes a set of control variables, namely Tobin's Q and cash flow.. Standard errors are clustered by firm and are reported in brackets. R^2 denotes adjusted R^2. The sample period is 1980 to 2006.

	(1)	(2)	(3)	(4)
$\log K_{i,t-1}$	-0.020	-0.071	-0.066	-0.050
	[0.002]***	[0.006]***	[0.006]***	[0.005]***
$Q_{i,t-1}$			0.061	0.046
			[0.006]***	[0.006]***
$CF_{i,t-1}$				0.096
				[0.019]***
Observations	9,180	9,180	9,180	9,180
R^2	0.07	0.27	0.32	0.35
Firm FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes

Table 3
Variance Decomposition of Firm Investments

This table reports a variance decomposition for several specifications of the investment regression. The left-hand-side is end-of year capital expenditures scaled by beginning-of-year property, plant and equipment. The right-hand-side includes different combinations of firm fixed effects, year fixed effects, Tobin's *Q*, cash flow, and the natural logarithm of beginning-of-year capital stock. The table reports the Type III partial sum of squares for each effect in the model normalized by the sum across the effects, forcing each column to sum to one. R^2 denotes adjusted R^2. The sample period is 1980 to 2006.

Variable	(1)	(2)	(3)	(4)
Firm FE	0.80	0.73	0.62	0.61
Year FE	0.20	0.10	0.08	0.07
Log(K)		0.17	0.14	0.09
Tobin's *Q*			0.16	0.10
Cash Flow				0.13
R^2	0.22	0.27	0.32	0.35

Table 4
Firm Size and Financial Constraints

This table reports estimates from regressions of the type:

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_i + \beta \log K_{i,t-1} + \phi \mathbf{X}_{i,t-1} + \rho_1 D_{index} + \rho_2 D_{index} \times \log K_{i,t-1} + \rho_3 D_{index} \times \mathbf{X}_{i,t-1} + \gamma_t + \varepsilon_{it},$$

where the left-hand-side is the end-of year capital expenditures scaled by beginning-of-year property, plant and equipment. The right-hand-side variables include firm fixed effect and year fixed effects, the log of the firm's capital stock, D_{index} is an indicator variable set equal to one based on the distribution of the Kaplan-Zingales (1997) KZ index, the Whited-Wu (2006) WW index, or the Hadlock-Pierce (2010) SA index, and $X_{i,t-1}$ is a set of additional control variables, namely Tobin's Q and cash flow. Specifications (2) through (4) set the dummy variable equal to one if the value of the index for a particular firm is below the median of the distribution. Specifications (5) through (7) set one dummy equal to one if the index for a particular firm is below the first quartile and another dummy equal to one if the index exceeds the third quartile of the distribution. R^2 denotes adjusted R^2. Standard errors clustered at the firm level are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log K	-0.050	-0.064	-0.051	-0.053	-0.059	-0.052	-0.052
	[0.005]***	[0.007]***	[0.005]***	[0.006]***	[0.006]***	[0.005]***	[0.005]***
Q	0.046	0.041	0.057	0.047	0.049	0.050	0.050
	[0.006]***	[0.022]***	[0.024]***	[0.008]***	[0.007]***	[0.008]***	[0.006]***
CF	0.096	0.054	0.057	0.089	0.083	0.166	0.090
	[0.019]***	[0.007]**	[0.008]***	[0.020]***	[0.020]***	[0.021]***	[0.009]***
Low WW$\times$ log K		0.008					
		[0.008]					
Low KZ$\times$ log K			-0.000				
			[0.003]				
Low SA$\times$ log K				0.002			
				[0.002]			
$WW_{Q25}\times$ log K					-0.011		
					[0.009]		
$WW_{Q75}\times$ log K					-0.012		
					[0.009]		
$KZ_{Q25}\times$ log K						-0.002	
						[0.004]	
$KZ_{75}\times$ log K						0.001	
						[0.003]	
$SA_{Q25}\times$ log K							0.001
							[0.001]
$SA_{75}\times$ log K							-0.005
							[0.007]
Observations	9,180	9,180	9,180	9,180	9,180	9,180	9,180
R^2	0.35	0.39	0.40	0.42	0.40	0.41	0.42

Table 5
Industry Returns to Scale and Firm Size Estimates

Two-Digit SIC	Industry	$\hat{\theta}_k$	$se(\hat{\theta}_k)$	$\hat{\beta}_k$	$se(\hat{\beta}_k)$
01	Agricultural Production Crops	0.443	0.031	-0.008	0.081
13	Oil and Gas Extraction	0.454	0.062	-0.014	0.004
14	Mining and Quarrying of Nonmetallic Minerals	0.442	0.141	-0.125	0.018
16	Heavy Construction	0.170	0.071	-0.193	0.014
20	Food and Kindred Products	0.437	0.032	-0.067	0.003
21	Tobacco Products	-0.039	0.189	-0.169	0.028
22	Textile Mill Products	0.492	0.131	0.041	0.057
23	Apparel	0.884	0.086	-0.048	0.008
24	Lumber and Wood Products	0.263	0.124	-0.057	0.006
25	Furniture and Fixtures	0.584	0.072	-0.021	0.009
26	Paper and Allied Products	0.245	0.052	-0.177	0.009
27	Printing, Publishing, and Allied Industries	0.540	0.099	-0.058	0.005
28	Chemicals and Allied Products	0.545	0.086	-0.027	0.002
29	Petroleum Refining and Related Industries	0.260	0.073	-0.036	0.003
30	Rubber and Miscellaneous Plastics	0.755	0.110	-0.028	0.005
31	Leather and Leather Products	0.128	0.071	-0.155	0.068
32	Stone, Clay, Glass, and Concrete Products	0.347	0.075	-0.009	0.012
33	Primary Metal Industries	0.530	0.107	-0.143	0.004
34	Fabricated Metal Products	0.251	0.052	-0.102	0.023
35	Industrial and Commercial Machinery	0.499	0.043	-0.071	0.008
36	Electronic Equipment and Components	0.677	0.061	-0.074	0.003
37	Transportation Equipment	0.185	0.052	-0.045	0.003
38	Photographic, Medical, and Optical Goods	0.379	0.066	-0.107	0.008
39	Miscellaneous Manufacturing Industries	-0.062	0.080	-0.126	0.020
40	Railroad Transportation	0.128	0.098	-0.029	0.003
42	Motor Freight Transportation and Warehousing	0.728	0.086	0.015	0.010
44	Water Transportation	0.673	0.100	-0.088	0.017
45	Air Transportation	0.670	0.071	-0.035	0.010
47	Transportation Services	0.121	0.094	-0.216	0.039
48	Communications	0.080	0.066	-0.056	0.004
50	Wholesale Trade-Durable Goods	0.468	0.094	-0.053	0.006
51	Wholesale Trade-Nondurable Goods	0.166	0.062	-0.152	0.012
52	Building Materials	0.628	0.135	-0.035	0.026
53	General Merchandise Stores	0.776	0.080	-0.037	0.016
54	Food Stores	0.361	0.057	-0.098	0.008
55	Automotive Dealers and Gasoline Stations	0.230	0.065	-0.035	0.033
56	Apparel and Accesory Stores	0.864	0.208	-0.056	0.023
57	Home Furniture and Furnishings Stores	0.196	0.104	-0.163	0.035
58	Eating and Drinkign Places	0.367	0.067	-0.011	0.004
59	Miscellaneous Retail	0.583	0.061	-0.004	0.014
70	Hotels and Other Lodging Places	0.689	0.153	-0.046	0.008
72	Personal Services	0.631	0.150	-0.102	0.022
73	Business Services	0.137	0.047	-0.070	0.006
75	Automotive Repair and Services	0.365	0.150	-0.059	0.084
79	Amusement and Recreation Services	0.059	0.096	-0.103	0.070
80	Health Services	0.622	0.160	-0.057	0.006
99	Nonclassifiable Establishments	0.663	0.175	-0.028	0.006

Table 6

Firm Size and Technological Returns to Scale

This table reports estimates from regressions of the type:

$$\beta_k = \alpha_1 + \alpha_2 \theta_k + \varepsilon_k,$$

where the left-hand-side variable is the industry-level firm size estimate, β_k, computed as the coefficient on the log of firm size from an investment regression including fixed effects and a set of control variables. We use no control variables for the unconditional β_k estimates used in Panel A. We include Tobin's Q and cash flow for the conditional β_k estimates used in Panel B. The right-hand-side variable is the estimate of technological returns to scale, θ_k, from a log-linear quasi-differenced revenue regression on firm size. Appendix B provides estimation details. In Specifications (1) and (3), both the size effect and technological returns to scale estimates are obtained from a panel of firms using firm-level data within each two-digit SIC industry. In Specifications (2) and (4), both the size effect and technological returns to scale estimates are obtained using industry-aggregated data at the two-digit SIC level. Standard errors are reported in brackets, and standard errors adjusted for the sampling variation in generated regressors are reported in parenthesis.

	A: Unconditional β		B: Conditional β	
	(1)	(2)	(3)	(4)
	Firm-Level	Industry	Firm-Level	Industry
θ_k	0.119	0.120	0.120	0.122
	[0.046]**	[0.047]**	[0.032]***	[0.031]***
	(0.061)*	(0.063)*	(0.056)**	(0.055)**
N	47	47	47	47
R^2	0.13	0.13	0.15	0.15

Table 7
Simulated Moments Estimation

This table reports results from SMM estimation of the investment model based on the balanced sample of US firms for the period 1980 to 2006. Panel A reports the simulated and estimated moments along with the t-statistics for their differences. Panel B reports the estimated structural parameters, with standard errors in parentheses. γ is the capital adjustment cost parameter; θ is the curvature of the profit function; and ρ and σ denote the serial correlation and standard deviation of profit shocks, respectively. The J-test is the χ^2 test for the overidentifying restrictions of the model, with its p-value reported below in parenthesis.

Panel A: Moments

	Actual Moments	Simulated Moments	t-Stats
Average of Tobin's Q (V/K)	1.571	1.578	0.215
Variance of Tobin's Q (V/K)	0.414	0.378	−1.045
Variance of Cash Flow (π/K)	0.125	0.125	0.011
Variance of Investment (I/K)	0.022	0.023	0.604
Serial Correlation of Investment (I/K)	0.309	0.268	−1.795

Panel B: Parameter Estimates

γ	θ	ρ	σ	J-Test
1.132	0.912	0.463	1.040	4.964
(0.048)	(0.005)	(0.021)	(0.048)	(0.026)

Table 8
Simulated Investment Regressions

This table reports results of investment regressions from simulations of the baseline model. We simulate 10 artificial panels of 340 firms each with 270 years of data. We estimate the investment regressions using the last 27 years of simulated data, which corresponds to the time span of the balanced sample from Compustat. We report the average coefficient estimates and standard errors across artificial panels. Panel A reports the unconditional size effect estimates. Panel B reports the conditional size effect estimates for different values of measurement error in Tobin's Q. The variance of the measurement error is expressed as percentage of the variance of Tobin's Q in simulated data.

Panel A: Unconditional Size Effects

	Data	Simulations
Firm Size ($\ln K$)	-0.071	-0.050
	$(0.006)^{***}$	$(0.003)^{***}$

Panel B: Conditional Size Effects

		Measurement Error (%)			
		0.10	0.15	0.20	0.25
	Data	Simulations			
Tobin's Q (V/K)	0.046	0.087	0.059	0.045	0.035
	$(0.006)^{***}$	$(0.008)^{***}$	$(0.006)^{***}$	$(0.005)^{***}$	$(0.004)^{***}$
Cash Flow ($/K$)	0.096	0.166	0.208	0.231	0.246
	$(0.019)^{***}$	$(0.028)^{***}$	$(0.026)^{***}$	$(0.025)^{***}$	$(0.024)^{***}$
Firm Size ($\ln K$)	-0.050	-0.042	-0.053	-0.060	-0.064
	$(0.005)^{***}$	$(0.005)^{***}$	$(0.004)^{***}$	$(0.004)^{***}$	$(0.004)^{***}$

Table 9
Simulated Variance Decomposition

This table reports the variance decomposition of the conditional investment regression from simulations of the baseline model. We simulate 10 artificial panels of 340 firms each with 270 years of data. We estimate the conditional investment regression and perform the variance decomposition using the last 27 years of simulated data, which corresponds to the time span of the balanced sample from Compustat. We compute the Type III partial sum of squares for each effect in the model normalized by the sum across the effects, forcing each column to sum to one. We report the average Type III partial sum of squares and adjusted R^2 for different values of measurement error in Tobin's Q. The variance of the measurement error is expressed as percentage of the variance of Tobin's Q in simulated data. The column "Data" reports for comparison the *within*-variance decomposition of the conditional investment regression in actual data.

		Measurement Error (%)			
		0.10	0.15	0.20	0.25
	Data	Simulations			
Tobin's Q (V/K)	0.31	0.41	0.20	0.11	0.07
Cash Flow (π/K)	0.42	0.45	0.63	0.72	0.76
Firm Size ($\ln K$)	0.27	0.14	0.17	0.17	0.17
R^2	0.22	0.56	0.55	0.55	0.54

Table 10
Firm Size and Technological Returns to Scale

This table reports results of investment regressions from simulations of the baseline model for different values of the curvature of the profit function (θ). We simulate 10 artificial panels of 340 firms each with 270 years of data. We estimate the investment regressions using the last 27 years of simulated data, which corresponds to the time span of the balanced sample from Compustat. We report the average coefficient estimates across artificial panels. Panel A reports the unconditional size effect estimates. Panel B reports the conditional size effect estimates for different values of measurement error in Tobin's Q. The variance of the measurement error is expressed as percentage of the variance of Tobin's Q in simulated data.

		Measurement Error (%)			
		0.10	0.15	0.20	0.25
Curvature (θ)	A: Unconditional β	B: Conditional β			
0.60	-0.087	-0.066	-0.091	-0.104	-0.113
0.70	-0.074	-0.055	-0.078	-0.089	-0.097
0.80	-0.063	-0.047	-0.066	-0.076	-0.082
0.90	-0.048	-0.038	-0.051	-0.058	-0.062
0.95	-0.027	-0.030	-0.034	-0.037	-0.038
0.99	-0.005	-0.003	-0.004	-0.005	-0.005

Table A.1
Summary Statistics

This table reports summary statistics for the primary variables used in the empirical analysis. Investment is defined as capital expenditures in property, plant and equipment scaled by the beginning-of-year capital stock. The capital stock is defined as net property, plant and equipment. Tobin's Q is defined as the market value of assets scaled by the book value of assets. Cash flow is calculated as the sum of end-of-year earnings and depreciation scaled by the beginning-of-year capital stock. Firm size is the natural logarithm of the beginning-of-year capital stock. The summary statistics are reported for each of three samples: the unbalanced sample of US firms from Compustat, the balanced panel of US firms from Compustat, and an international sample of eight countries (Australia, Brazil, Canada, France, Germany, Japan, South Korea, and the United Kingdom) from the Worldscope database.

Panel A: Unbalanced Sample				
Variable	Obs.	Mean	Median	Std. Dev.
Investment	130,108	0.301	0.213	0.298
Tobin's Q	130,108	1.550	0.966	2.917
Cash Flow	130,108	0.517	0.332	0.889
Firm Size	130,108	3.562	3.408	2.341
Panel B: Balanced Sample				
Variable	Obs.	Mean	Median	Std. Dev.
Investment	9,180	0.233	0.196	0.170
Tobin's Q	9,180	1.571	1.321	0.820
Cash Flow	9,180	0.425	0.327	0.489
Firm Size	9,180	5.328	5.282	2.182
Panel C: International Sample				
Variable	Obs.	Mean	Median	Std. Dev.
Investment	62,745	0.245	0.149	0.365
Tobin's Q	62,745	1.016	0.678	1.446
Cash Flow	62,745	0.377	0.203	1.981
Firm Size	62,745	13.008	12.920	3.807

Table A.2
Measurement Error and Selection Bias

This table reports estimates from regressions of the type:

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_i + \beta \log K_{i,t-1} + \phi X_{i,t-1} + \gamma_t + \varepsilon_{it},$$

where the left-hand-side is end-of year capital expenditures scaled by beginning-of-year property, plant and equipment. The right-hand-side variables include a firm fixed effect, α_i, year fixed effects, γ_t, $\log K_{i,t-1}$ is the natural logarithm of beginning-of-year capital stock, and $X_{i,t-1}$ denotes a set of control variables, namely Tobin's Q and cash flow. Specifications (1)–(2) report instrumental variables estimation results using lagged Q and cash flow as instruments for Tobin's Q. Specification (3) reports the reverse regression estimates using the methodology of Erickson and Whited(2005). The results from the reverse regression are re-arranged in the table to put investment on the left hand side. Specification (4) uses an alternative measure of Tobin's Q based on earnings forecasts from securities analysts as in Cummins, Hassett and Oliner, (2006). Specification (5) reports the second-stage estimation results from a Heckman type procedure, where the first stage models the probability of exiting the Compustat database as a function of firm size, Tobin's Q, cash flow, cash holdings, and leverage. R^2 denotes adjusted R^2. Standard errors are clustered by firm and are reported in brackets.

	(1)	(2)	(3)	(4)	(5)
$\log K_{i,t-1}$	-0.043	-0.050	-0.056	-0.048	-0.048
	[0.005]***	[0.005]***	[0.008]***	[0.004]***	[0.005]***
$Q_{i,t-1}$	0.049	0.045	1.110	0.008	0.049
	[0.010]***	[0.009]***	[0.128]***	[0.001]***	[0.007]***
$CF_{i,t-1}$	0.105	0.092	-0.554	0.141	0.101
	[0.012]***	[0.014]***	[0.008]***	[0.017]***	[0.019]***
Inv. Mills Ratio					-0.001
					[0.004]
Observations	8,840	8,840	9,180	8,252	9,180
R^2	0.35	0.36	0.44	0.58	0.35
Instruments	$CF_{i,t-2}$	$CF_{i,t-2}$, $Q_{i,t-2}$			

Table A.3
Additional Robustness Tests

This table reports robustness estimates from variations of the baseline regression:

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_i + \beta \log K_{i,t-1} + \phi X_{i,t-1} + \gamma_t + \varepsilon_{it},$$

where the left-hand-side is end-of year capital expenditures scaled by beginning-of-year property, plant and equipment. The right-hand-side variables include firm fixed effects, α_i, year fixed effects, γ_t, $\log K_{i,t-1}$ is the natural logarithm of beginning-of-year capital stock, and $X_{i,t-1}$ denotes a set of control variables, namely Tobin's Q and cash flow. Specification (1) includes $\log K_{i,t-2}$ in place of $\log K_{i,t-1}$. Specification (2) includes contemporaneous Tobin's Q and cash flow. Specification (3) includes additional lags of Tobin's Q and cash flow. Specification (4) reports the estimates from an Arellano-Bond dynamic panel-data regression including lagged investment. Specification (5) includes firm age, defined as the number of years since a firm became public. Specification (6) includes cash holdings, book leverage, return on assets, and a dividend payer dummy. Specification (7) includes squared and interaction terms for the control variables (not reported). Specification (8) reports estimates based on a large unbalanced panel of US firms from Compustat for the period 1962-2006. Standard errors are clustered by firm and are reported in brackets. R^2 denotes adjusted R^2.

Table A.3
Additional Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log K_{t-1}		-0.051	-0.050	-0.132	-0.050	-0.051	-0.052	-0.081
		[0.005]***	[0.005]***	[0.004]***	[0.005]***	[0.005]***	[0.006]***	[0.002]***
$Q_{i,t-1}$	0.047	0.044	0.050	0.068	0.046	0.03	0.072	0.032
	[0.006]***	[0.006]***	[0.007]***	[0.005]***	[0.006]***	[0.006]***	[0.010]***	[0.001]***
$CF_{i,t-1}$	0.079	0.102	0.109	0.151	0.096	0.08	0.219	0.088
	[0.018]***	[0.014]***	[0.014]***	[0.006]***	[0.019]***	[0.017]***	[0.028]***	[0.002]***
log K_{t-2}	-0.059							
	[0.005]***							
$Q_{i,t}$		0.002						
		[0.006]						
$CF_{i,t}$		-0.005						
		[0.004]						
$Q_{i,t-2}$			-0.007					
			[0.006]					
$CF_{i,t-2}$			-0.013					
			[0.006]**					
$I_{i,t-1}/K_{i,t-2}$				0.019				
				[0.010]*				
Age					-0.006			
					[0.015]			
Cash						-0.071		
						[0.029]**		
Leverage						0.007		
						[0.009]		
ROA						0.412		
						[0.046]***		
Dividend Payer						0.033		
						[0.010]***		
Observations	9,180	9,180	8,840	8,840	9,180	9,180	9,180	130,108
R^2	0.35	0.36	0.35	0.39	0.35	0.38	0.39	0.41

Table A.4
Firm Size in Corporate Investment: International Evidence

This table reports estimates from regressions of the type:

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_i + \beta \log K_{i,t-1} + \phi X_{i,t-1} + \gamma_t + \varepsilon_{it},$$

where the left-hand-side is end-of year capital expenditures scaled by beginning-of-year property, plant and equipment. The right-hand-side variables include a firm fixed effect, α_i, year fixed effects, γ_t, $\log K_{i,t-1}$ is the natural logarithm of beginning-of-year total capital stock, and $X_{i,t-1}$ denotes a set of control variables, namely Tobin's Q and cash flow. R^2 denotes adjusted R^2. Standard errors are clustered by firm and are reported in brackets.

	Australia	Brazil	Canada	France	Germany	Japan	South Korea	United Kingdom
$\log K_{i,t-1}$	-0.036	-0.012	-0.036	-0.040	-0.043	-0.016	-0.033	-0.034
	[0.004]***	[0.006]**	[0.003]***	[0.004]***	[0.005]***	[0.002]***	[0.005]***	[0.002]***
$Q_{i,t-1}$	0.061	0.033	0.074	0.088	0.081	0.060	0.098	0.059
	[0.007]***	[0.020]*	[0.006]***	[0.013]***	[0.013]***	[0.006]***	[0.014]***	[0.003]***
$CF_{i,t-1}$	0.026	0.053	0.011	0.036	0.033	0.036	0.025	0.022
	[0.004]***	[0.012]***	[0.005]**	[0.011]***	[0.006]***	[0.006]***	[0.009]***	[0.003]***
Observations	5,564	1,533	7,931	4,559	2,998	19,241	3,964	18,598
R^2	0.31	0.49	0.36	0.39	0.40	0.37	0.36	0.35